FEMALE BODY TYPES CLASSIFED BY WAIST-TO-HIP AND REGIONAL FAT DISTRIBUTION RATIOS

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Body type classification is employed to determine disease risk using measurements such as Waist-to-Hip Ratio (WHR) and waist circumference. However, these measures classify body types using *a priori* determined cut-points. The purpose of this investigation was to establish data-based cut-points denoting female body types ranging between android and hyper-gynoid using the WHR and regional body fat distribution-ratio (RFD-ratio). Waist, abdomen, and hip circumference, height, weight, and body fat were obtained for 73 Caucasian females. The waist and hip circumferences were used to determine the WHR classification. The abdomen circumference, height, and BMI were used to develop the RFD-ratio classification. The subjects were 20.93 ± 1.95 years old, weighed 62.31 ± 9.92 kg, and were 163.78 ± 6.70 cm tall. They had a BMI of 23.19 ± 3.21 kg·m^{-2} and a body fat percentage of 25.85 ± 6.59. A TwoStep cluster analysis was used to determine the number of "naturally" formed body type clusters. The analysis was conducted with no *a priori* determination of number of clusters to form, where to make the cut-points, or how many subjects to place in each cluster. Within both body type classification systems (ie. WHR and RFD-ratio), three good quality clusters formed. For the WHR system, the cut-point between the hyper-gynoid and gynoid clusters fell at 0.72, while the cut-point between the gynoid and android clusters was 0.78. For the RFD-ratio system, the cut-

points were 0.68 and 0.78, respectively. To examine interchangeability between systems, the WHR and RFD-ratio system's values were compared using a One-Factor ANOVA. Ratios differed ($p < 0.01$) between systems. This indicated that the two systems could not be used interchangeably despite having a correlation of $r = 0.65$. It was concluded that both classification systems can be used to determine female body type. Owing to application simplicity, the WHR classification system may be preferable. Further examination of the subjects' health status as well as testing a larger number of overweight or obese subjects is required to broaden generalizability of the two body type classification systems.

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1.0 INTRODUCTION

In the early 1950's, Vague investigated the relation between body fat distribution and the prevalence of metabolic and cardiovascular diseases (53). Prior to this research, it was assumed that simply being obese, regardless of the anatomical distribution of the adipose tissue, increased the prevalence of these diseases. Through this early work, and the research that followed, it has been determined that in addition to obesity, body fat distribution differentially influences the incidence of metabolic and cardiovascular diseases (3,25,34,35,37,39,56). For obese individuals, those with a greater amount of abdominal fat are at a higher disease risk than those with a greater amount of lower body fat. As an extension of this previous research, the present investigation established data-based cut-points describing the range of female body types between hyper-android and hyper-gynoid using continua derived from Waist-to-Hip Ratio (WHR) and regional body fat distribution ratio (RFD-ratio).

At the same time Vague (53) was examining the differential effects of body fat distribution on disease risk, Sheldon's (12) work on somatotyping was also gaining interest. Sheldon's methodology of somatotyping determines an individual's physique (or shape) based on fat quantity, muscular robustness, and height compared to body weight (12). While combining body physique and fat distribution into one classification system is not a new concept, it is one that has yet to be fully explored. Body shape is heavily reliant on fat distribution, and though fat distribution is more closely linked to disease-risk, body shape is more recognizable by the general population. It was proposed in the present investigation that merging these two measurements could form a new “body type” classification system, one that matches an individual’s body shape to a particular fat distribution pattern (i.e. gynoid or android). This system would allow weight management programs and/or disease-risk categories to be developed based on specific body types defined along a data-based of body fat continua.

Most studies of the relation of anatomical fat distribution to disease-risk have two major limitations. First, almost all studies focus on overweight or obese subjects, and devote little attention to normal-weight individuals. This lack of attention to normal-weight individuals limits implementation of preventative medicine protocols. These protocols would identify those who may fall into the established “at-risk” disease categories, but who presently do not have a high body mass index (BMI). Second, when determining body types, the vast majority of fat distribution studies arbitrarily pre-determine which subjects fit into which group. Either a finite number of subjects are assigned to each fat distribution group, or the quantity of the sample is used to create equal group size.

It seemed important to identify a methodological approach that remedied the above mentioned measurement limitations. The first methodological issue to resolve entailed determining body type categories that are not *a priori* determined, but rather are based on uniform clustering of the data. Two types of regional fat distribution are commonly referred to within exercise and anthropometric literature – android and gynoid. Android fat distribution is typically associated with male fat patterning (predominantly upper body fat), while gynoid fat distribution refers to female fat patterning (predominantly lower body fat); although females can also present android fat patterning (53). As body type can differ between sexes, it was also imperative that males and females be studied and grouped separately, according to their sex specific clustering of fat measurements. The present study focused on female body types as determined by differences in anatomical fat distribution.

Despite the common use of only two body types in previous research, it is possible that more may exist. Krotkiewski and colleagues introduced a third body type (i.e. “intermediate”) when creating a new fat distribution system for females. This intermediate body type fell between those with predominately lower body fat distribution and those with predominately upper body fat distribution (35). More convincingly, Newell-Morris et al. using a k-means statistical cluster analysis for an all male sample, identified four body types – one predominately gynoid, one excessively android, and two other types displaying more android characteristics (45). Newell-Morris et al. demonstrated that a cluster analysis can be used to identify multiple body types independent of investigator determined classifications.

Waist-to-hip ratio (WHR) and waist circumference are two commonly used anthropometric measures that are influenced by body fat distribution (1,14). Both of these measures are used to predict an individual’s metabolic and cardiovascular disease risk. Waist-to-hip ratio is calculated by dividing the waist circumference by the hip circumference. The waist circumference measures the girth of the abdomen. For women, the “at-risk” WHR category is 0.80 and higher, while the “at-risk” category according to waist circumference is 88 cm and higher (1).

The problem with the application of WHR and waist circumference categories, especially when only the latter is measured, is that the focus predominately falls on the overweight or obese population. It is recognized that overall, these individuals may be at a higher disease risk than leaner individuals. However, the data provided by Hartz et al. succinctly details why fat distribution may have a comparatively bigger impact on disease risk (Figure 1). In their study, Hartz et al. first divided subjects into four groups based on WHR: ≤ 0.72, 0.73 to 0.76, 0.77 to 0.80, and ≥ 0.81. Subjects were then categorized by levels of obesity based on percent over ideal weight (as listed in the Metropolitan Life Insurance tables): non-obese (<21%), moderately-obese (21-50%), and severely-obese (>50%). It was found that the percentage of diabetics was similar between non-obese subjects whose WHR was 0.81 or higher and the severely-obese subjects with a WHR of 0.72 or less (25).

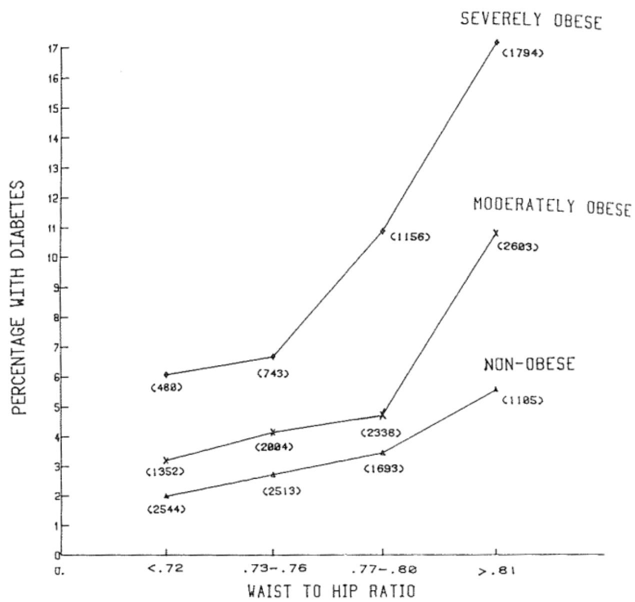

FIGURE 1: Prevalence of diabetes according to obesity classification and fat distribution (25).

Numerous studies have shown that as both the level of obesity and WHR rises, there is an increase in the prevalence of metabolic and cardiovascular disease (3,25,34,35,37,39,56). However, the Hartz et al. study points out why it is critical to examine and clearly define which body types (and how many) exist, and to identify the relation between each body type and the prevalence of disease occurrence.

It is advantageous to use WHR and waist circumference when examining fat distribution due to their ease of measurement and that the general population can perform their own measurements of these variables. Because these relatively simple methods do not require the expertise of health or exercise professionals, they are ideal for increasing the interest and adherence of the general population to exercise and dietary intervention programs. Never-the-less, while these methods may be among the most practical, their simplicity of assessment can be a limitation, i.e. they employ only body circumference measurements, not the measurement of the actual amount of fat. However, there is a strong correlation between circumference measures and total body fat mass (48).

Currently, the most precise method of determining regional body fat is dual-energy x-ray absorptiometry (DXA). This procedure can accurately measure the quantity of adipose tissue found in a specific body region. Unfortunately, DXA is expensive and typically only found in a laboratory or clinical setting. In lieu of such a costly and relatively inaccessible system, regional fat distribution can be estimated through anthropometric equations such as those developed by Ritchie and Davidson (48). These equations are based on body circumferences, body mass index (BMI), height, and weight and all show strong correlations to regional body fat determined by DXA.

The present investigation examined two separate body type continua, i.e. one based on WHR and one based on a regional fat distribution ratio (RFD-ratio). These two classification systems are based on underlying fat distribution and are both strongly correlated with the prevalence of metabolic and cardiovascular disease (23,35). A body type continuum based on WHR would be advantageous due to its ease of use. The determined value could then be used conjunctively with the body types based on a regional fat distribution ratio, which is more closely linked to the amount of anatomically specific adipose tissue.

An additional benefit of establishing body type categories based on fat distribution methods involves individualizing weight management plans. As an example, studies involving dietary caloric restriction have shown that those females with android-type obesity are able to lose more weight than those with gynoid-type obesity within the same time period (22,29). This may be due, in part, to the metabolic and structural differences in adipose tissue found in the abdomen (i.e. android type) versus that found in the gluteal-femoral (i.e. gynoid type) region (34,35). Once again, establishing body types based on fat distribution can help in developing diet and exercise programs.

As differences in anatomical fat distribution have been observed between ethnic groups (44) as well as between pre-, peri-, and post-menopausal women (33) the present study focused only on Caucasian females ages 18-29 years old. Any individuals with diseases (i.e. Polycystic Ovarian Syndrome) or taking medications known to affect normal fat distribution were not included in the study. This study employed a cross-sectional design, sampling subjects from a population that included a wide range of BMIs.

1.1 STATEMENT OF PURPOSE

The purpose of the present investigation was to develop a data-driven continuum of body types ranging from android to gynoid fat distribution based on WHR and a RFD-ratio for pre-menopausal women. Statistical clustering models were used to develop two body type classification continua, i.e. one based on WHR and one based on RFD-ratio.

2.0 LITERATURE REVIEW

The present investigation aimed to determine cut-points along continua for various female body types based on WHR and a RFD-ratio. In order to confirm the importance of such undertaking as well as to determine the appropriate methods for the investigation, it was imperative to find rationale in the literature. Critical areas of review included the importance of regional body fat distribution and its association with obesity-related diseases, determining the strongest anthropometric measures for regional fat distribution prediction, and previous developments of body type classification systems.

2.1 IMPORTANCE OF REGIONAL BODY FAT DISTRIBUTION

The association between regional body fat distribution (RFD) and disease-related risk was first recognized by Vague in the early 1950's (53). Vague hypothesized that it was not solely obesity that was the driving factor for disease risk, but the activity of adiposity as controlled through neurohormonal mechanisms was also important. After creating the first RFD scale, Vague tested his hypothesis by comparing the prevalence of diseases such as diabetes and atherosclerosis within five RFD categories: hypergynoid, gynoid, intermediate, android, and hyperandroid.

Vague found that 35% of hyperandroid females were diagnosed with diabetes. The percentage fell to 25% in the android category, followed by 7%, 2%, and 1% in the remaining three categories as the predominate fat location moved from the waist to the hips. A similar, but more pronounced relation between predominate adipose tissue location and disease risk occurred when investigating coronary artery disease (CAD). One hundred percent of hyperandroid and android women that were studied had CAD, with the level dropping to 50% in the intermediate group, 10.6% in the gynoid group and only 1.7% in the hypergynoid group. Vague's (53) study was the first to show a relation between the anatomical location of fat and the prevalence of chronic disease. Since this first study appeared, a multitude of additional studies have been performed to further support the relation between RFD and prevalence of disease (8,11,13,20,21,25,37,39,47,49,51,55,57,59).

2.1.1 Association between RFD and Disease

From the beginning, studies investigating the link between RFD and obesity focused primarily on known obesity-related disorders: diabetes, cardiovascular disease (CVD), stroke, gallbladder disease, and those clinical elements associated with the development of these diseases such as hypertension and elevated lipids, glucose, and insulin levels. In the early 1980's, simplified anthropometric measures were developed, such as WHR. These measures helped to more easily identify those with upper body fat distribution versus lower body fat distribution for use in research that defined disease risk (11,20,21,24,25,30,35,37,57,59).

Hartz and colleagues (24) used this new body fat index in a study investigating the association between RFD, obesity, and diabetes. Subjects were first divided into subgroups based on WHR and then again by obesity level. It was found that those females in the highest WHR quartile had a threefold increase in risk of diabetes as compared to those in the lowest quartile at a comparable level of obesity. When examining women in the upper quartile of both WHR and obesity classifications, the risk of diabetes was 10.3 times greater than non-obese subjects in the lowest WHR category. Using similar methods as Hartz et al., other studies (11,21,24,25,51) have examined the correlation between diabetes and RFD. These studies have determined that the relative risk (RR) for those women with high WHR ranged from 2.15 (51), to as high as 7.5 (11) (Table 1). A recent meta-analysis (55) involving 32 studies determined a pooled RR of 3.0 for diabetes for women in the highest WHR group versus the reference group.

The correlation between body fat distribution and CVD has also been investigated (21,37,47,59). These investigations examined CVD in general as well as by more specific diagnoses, such as stroke or myocardial infarction (MI). Relative risk values for CVD and its specific diagnoses ranged from 1.7 (21) to 8.2 (37) when expressed according to WHR, as shown in Table 2. A meta-analysis performed by de Koning et al. (14) showed a minimally adjusted pooled RR for CVD of 2.50 for women (maximally adjusted RR was 2.19).

Relative risk values, however, can be somewhat misleading as they vary depending on what adjustments are used to control confounding variables. As such, another method of evaluating the impact of RFD on disease risk is to examine prevalence across obesity subgroups as defined by WHR. If the prevalence across subgroups remains relatively constant, then the subgrouping is a poor indicator of the correlation between the RFD and disease risk. Conversely, if the prevalence rises or falls significantly between subgroups in a linear or exponential trend, then an association can be made between RFD and disease risk.

TABLE 1: Relative risk for diabetes in highest subgroup of women based on WHR*

Reference	Risk Ratio	Adjustments	WHR Subgroup	Age of sample (years)
Snijder et al. (51)	2.15	Age	N/A	50-75
Hartz et al. (25)	3.09	Age, relative weight	Four groups: <0.72, 0.73-0.76 0.77-0.80 >0.81	40-59
Hartz et al. (24)	3.15 10.34 (WHR & BMI)*	Obesity	Quartiles	40-59
Carey et al. (11)	3.3 7.5	Age, family history of diabetes, exercise, smoking, intakes of saturated fat, calucium, potassium, and magnesium, and glycemic index Age	Six groups: <0.72, 0.72-0.75 0.76-0.79 0.80-0.83 0.84-0.87 >0.88	30-55
Folsom et al. (21)	11.3 29.0 (WHR & BMI)*	Age, educational level, physical activity, alcohol intake, smoking status, pack-years of cigarette smoking (continuous), age at first live birth, estrogen use, vitamin use, high blood pressure, and daily calorie, whole grain, fruit, vegetable, fish and red meat intake	Quintiles	55-69

* Unless otherwise noted, certain studies investigated the cumulative effect of WHR and BMI on the relative risk factor for diabetes.

TABLE 2: Relative risk for cardiovascular disease (CVD) events for women based on WHR

Reference	Risk Ratio	Adjustments	WHR Subgroup	Age of sample (years)
Yusuf et al. (59)	1.75 (MI)[a, b]	Age, sex, smoking, region, BMI, apolipoproteins B and A, history of hypertension, history of diabetes, diet, activity, alcohol use, and psychosocial variables	Quintiles	Not listed
Folsom et al. (21)	1.9 (CHD)[c] 1.7 (other)	Age, educational level, physical activity, alcohol intake, smoking status, pack-years of cigarette smoking (continuous), age of first live birth, estrogen use, vitamin use, high blood pressure, and energy, whole grain, fruit, vegetable, fish and red meat intake	Quintiles	55-69
Rexrode et al. (47)	2.43 (CHD)[c]	BMI, age, smoking, parental history of MI, alcohol consumption, physical activity, menopausal status, hormone replacement therapy, oral contraceptive use, aspirin intake, saturated fat intake, antioxidant score, hypertension, diabetes, elevated cholesterol level	Six groups <0.72, 0.72 - <0.76, 0.76 - <0.80, 0.80 - <0.84, 0.84 - <0.88, ≥0.88	40-65
Lapidus et al. (37)	8.2 (MI)[b] 3.8 (stroke)	Age	Quintiles	38-60

[a] Odds Ratio, [b] Myocardial Infarction, [c] Coronary Heart Disease

Dalton et al. (13) investigated the association of BMI, WC, and WHR with CVD risk factors such as diabetes, hypertension, and dyslipidaemia. The disease prevalence was examined within *a priori* determined body weight categories. Subjects were divided into three body weight categories (normal, overweight, and obese), with the cut-points dependent on the obesity classification system (BMI, WC, or WHR). Those with a BMI < 25.0 $kg \cdot m^{-2}$ were classified as normal weight, 25.0-29.9 $kg \cdot m^{-2}$ as overweight, and ≥ 30.0 $kg \cdot m^{-2}$ as obese. Women with a WHR < 0.80 were categorized as normal, 0.80-0.84 as overweight, and ≥ 0.85 as obese. Regardless of the body weight classification system used, each CVD risk factor demonstrated an increase in prevalence as the body weight level increased (Table 3). This trend held when examining the prevalence of having one, two, or all three risk factors. Dalton et al. determined that WHR was the strongest predictor of having at least one of the three risk factors, although age-adjustment significantly attenuated the associations.

TABLE 3: Prevalence of CVD risk factors by BMI and WHR in Australian women (13)

	Type 2 diabetes		Hypertension		Dyslipidaemia		One or more factors	
Body Weight Category	BMI	WHR	BMI	WHR	BMI	WHR	BMI	WHR
Normal	2.8	2.2	16.3	16.3	12.8	11.0	25.6	24.0
Overweight	6.3	6.1	31.9	34.6	28.0	30.2	47.7	52.7
Obese	16.2	19.1	46.5	48.7	42.8	47.4	66.8	70.0

All values listed as percentages of total population studied.

A number of investigations have correlated anthropometric measures with disease incidence rates. An association between RFD and both hypertension and dyslipidaemia has been demonstrated either preceding or in the presence of these metabolic/circulatory disorders. The appearance of certain metabolic/circulatory markers such as hypertension and elevated glucose, insulin, and lipid levels is often seen prior to and during the development of obesity-related diseases. However, testing for these markers typically involves blood assays, laboratory time, and extra diagnostic cost. Several studies indicate that RFD has a moderately-strong correlation with hypertension and elevated fasting glucose, fasting insulin, and triglyceride levels (Table 4). Thus, it may be beneficial to use RFD as a general indicator of potential risk for diseases such as diabetes and CVD.

Examining both the relative risk and prevalence values it is clear that an association exists between RFD and certain diseases. Using the WHR classification of obesity gives a pooled RR of 3.0 for diabetes (55) and 2.50 for CVD (14). This indicates that WHR is a strong predictor of both diseases. The WHR is also moderately correlated with metabolic/circulatory variables such as hypertension, fasting insulin, fasting glucose, and triglyceride levels. However, WHR is not a strong predictor of other diseases, such as lung or colon cancer (21). This is because these diseases may be influenced more by environmental factors and genetics than obesity.

TABLE 4: CVD risk factors and association with RFD

Risk Factors	Dalton et al. (13)	Mundi et al. (43)	Kissebah et al. (34)		Kalkhoff et al. (30)		Seidell et al. (49)	Jensen et al. (28)	
		CT visceral[a]	UBSO[b]	LBSO[c]	UBSO[b]	LBSO[c]		UBSO	LBSO
Hypertension									
SBP (mm Hg)					136 ± 4[e]	125 ± 3			
DBP (mm Hg)					84 ± 2[d]	76 ± 2			
R	0.345 (SBP)				0.26 (SBP) 0.29 (DBP)		0.43 (SBP) 0.36 (DBP)		
Fasting Glucose (mg/dl)			97 ± 4	88 ± 5				94 ± 2	93 ± 1
R	0.309	0.35			0.24		0.40		
Fasting Insulin			34 ± 4[d] µIU/ml	20 ± 3 µIU/ml				10.9 ± 1.4[e] µU/ml	7.3 ± 0.5 µU/ml
R		0.52			0.18		0.45		
Cholesterol (mg/dl)			187 ± 8	183 ± 15	196 ± 12	212 ± 9		216 ± 6	209 ± 14
R							0.24		
Triglycerides (mg/dl)			156 ± 14[d]	79 ± 7	103 ± 24	72 ± 8		145 ± 21[f]	71 ± 8
R	0.406	0.59					0.40		
FFA					476 ± 34 µEq/L	501 ± 28 µEq/L		579 ± 44 µmol/L	412 ± 95 µmol/L

[a] Mundi et al. (43) investigated the correlation between visceral, subcutaneous, and leg fat and metabolic characteristics using computed tomography rather than using WHR or WC [b] UBSO = subjects with upper body segment obesity [c] LBSO = subjects with lower body segment obesity [d] Significantly greater than subjects with lower body fat distribution ($P < 0.01$) [e] Significantly greater than subjects with lower body fat distribution ($P < 0.05$) [f] Significantly greater than subjects with lower body fat distribution ($P < 0.001$)

2.1.2 Relation of RFD to cellular differences in adipose tissue

Although a correlation exists between RFD and certain disease states, it is important to understand the differences between abdominal and femoral adipose cells and how these differences relate to RFD. Despite the fact that abdominal and femoral adipose cells are similar in origin and perform the same function, cells from the two anatomical areas vary with respect to size, lipolysis rate, and effects of certain hormones.

While abdominal subcutaneous fat cell volume differs minimally between males and females (0.531 ± 0.27 vs. 0.599 ± 0.28 μg lipid/cell, respectively), the femoral fat cell size is significantly lower in males than females (0.596 ± 0.27 vs. 0.724 ± 0.23 μg lipid/cell, $P < 0.001$, respectively) (43). In general, women tend to have larger femoral fat cells than abdominal fat cells (34,35,43,50), with sizes up to 0.7-0.8 μg/cell (35). However, when considering RFD status, it has been found that women with upper body obesity have significantly greater abdominal fat cell volume compared to women who are nonobese or have lower body obesity. However, the volume of femoral fat cells does not differ between the groups (34).

It is well known that certain hormones and catecholamines such as epinephrine, norepinephrine, glucagon, growth hormone, testosterone, and cortisol trigger lipolysis, although only catecholamines have an acute stimulatory effect (58). Each hormone effects both abdominal and femoral fat cells, but the responses elicited differ. These variations are most likely due to the quantity and/or sensitivity of four adrenoreceptors found on the cell surface: β1, β2, β3, and α2. The β receptors are responsible for stimulating lipolysis, while the α receptors inhibit it (58).

To test the lipolytic response, baseline levels of palmitate, free fatty acids (FFA), insulin, and glucose have been evaluated, and then measured again during influxes of catecholamines, insulin, or glucose. At baseline, plasma palmitate and FFA concentrations did not differ significantly between upper body obese, lower body obese, and non-obese females (28,42). However, the palmitate and FFA flux was found to be significantly greater in upper body obese women than lower body or nonobese women (28,42). Fasting insulin levels were found to be significantly different between the three groups, with upper body obese women having the highest level and non-obese women having the lowest levels (28,34). Fasting glucose levels showed non-significant differences between the three groups (34).

Baseline levels of plasma palmitate, FFA, and glucose do not differ between obesity types. Never-the-less, creating influxes of catecholamines, insulin, and glucose allows investigators to determine if the cell location and/or RFD affects lipolysis. Increasing catecholamines (i.e. norepinephrine and epinephrine) produces a significant increase in lipolysis from abdominal cells with almost no change from femoral cells (34,50). Removing the α-adrenergic component in femoral cells through the use of phentolamine changes their lipolytic response to more closely resemble that from the abdominal cells. This indicates that the reduced lipolytic response found in femoral cells is most likely due to an increased number and/or sensitivity of α-adrenergic receptors (34). As lipolysis in abdominal cells rises with increasing concentrations of catecholamines, the anti-lipolytic effect of insulin also increases in these cells. Whereas, even a supramaximal concentration of insulin has no significant effect on the femoral fat cells (50).

Oral glucose timed tests are also used to determine the effect of increased intake of glucose on the plasma glucose and insulin levels. As demonstrated in Figure 2, women presenting with upper body obesity have significantly higher baseline plasma glucose and insulin levels throughout an oral glucose tolerance test (34,35). High levels of glucose and insulin found in upper body obese women during an oral glucose test indicates that some change in the glucose transporter type 4 receptors has occurred, but whether it is due to a lower sensitivity or reduced quantity is unknown.

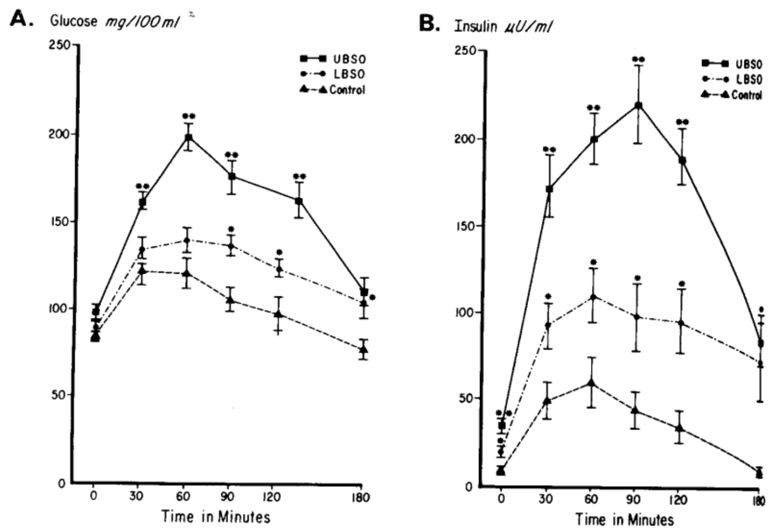

FIGURE 2: Effects on plasma glucose and insulin levels during oral glucose tests (34). UBSO: Upper Body Segment Obesity; LBSO: Lower Body Segment Obesity

Jensen et al. (28) used an insulin clamp procedure that can also be used to examine the lipolytic response in adipocytes. Providing a bolus of insulin significantly increased the plasma palmitate, FFA, and glucose concentrations in the two obese groups as well as normal weight controls. Both the lower and upper body obese groups were significantly higher than the non-obese group, although not from each other. Despite having a lower plasma insulin concentration during the insulin clamp procedure (9.3 ± 0.4, 11.5 ± 0.7, 17.6 ± 1.5 µU/ml, for the nonobese, lower body obese, and upper body obese groups, respectively), the nonobese women showed a greater glucose utilization and produced significantly less endogenous glucose than either obese group (28).

A wide array of hormones have been linked to fat cell localization. Cortisol has been shown to have lipid accumulating effects in the presence of insulin, though these effects can be negated by growth hormone. Growth hormone is also responsible for lipid mobilization. These effects are most pronounced in visceral fat cells due to the high density of glucocorticoid receptors found on these cells. Growth hormone can also accentuate the effects of testosterone, which inhibits lipoprotein lipase, the enzyme responsible for regulation of lipid accumulation, and glycerophosphate dehydrogenase. In women, this inhibition can cause an increase in the accumulation of visceral fat (7). Unbound, or free testosterone (%), has been found to be directly correlated with WHR ($r = 0.44$). Plasma sex hormone-binding globulin (SHBG) is inversely correlated with WHR ($r = -0.49$). An increased level of free testosterone and lower SHBG indicate an increase in degree of androgenic/estrogenic hormonal activity as the WHR increases (17). Other hormones, such as oestrogen, progesterone, estradiol, androstenedione, and dehydroepiandrosterone sulfate have also been investigated, but show no association or effect on adipose tissue metabolism or localization (7,17).

When studying RFD, it is not only important to recognize the effects and metabolic characteristics that are specific to fat cell localization, but also to understand why and how they occur on the cellular level. Even though femoral and abdominal fat cells are derived from the same tissue, they display remarkably different behaviors. Abdominal fat cells tend to be smaller (unless upper body obesity is present) and more sensitive to lipolytic stimulation from catecholamines, while femoral fat cells tend to be larger and less responsive, even at supramaximal concentrations (34). Those females with upper body obesity tend to have a higher level of insulin, glucose, palmitate, and FFA during influxes of catecholamines and glucose (28,34,35,42,50). This indicates that larger fat cells due to increased adipose storage have reduced insulin and carbohydrate metabolic function when compared to women who are non-obese or have lower body obesity. These differences are most likely due to variation in the number and sensitivity of β and α receptors found on the cell surface (58). Even though a large number of studies focused on the differences in obese and/or overweight subjects based on RFD, more recent research has found that similar cellular and metabolic abnormalities can also be found in certain normal weight individuals (15,16).

2.1.3 Rationale for examining normal weight individuals

As described above, Hartz et al. (25) found that non-obese subjects with a high WHR (> 0.81) had a similar prevalence of diabetes as those severely obese subjects with a low WHR (< 0.72). The finding is somewhat incongruous as a higher disease-risk is usually associated with obese individuals. However, Folsom et al. (21) reported similar findings, showing that those individuals in the lowest BMI and highest WHR quintiles had a non-significantly different RR for diabetes than those individuals in the highest BMI and lowest WHR quintiles (11.5 and 13.8, respectively) (Figure 3). This further supports the hypothesis that WHR plays a part in the development of obesity-related diseases, and that those individuals with a high WHR may be at risk, even in the absence of obesity.

This trend is not only found in diabetes, but with CVD as well. Folsom et al. also showed that women in the highest quintile of WHR actually had a higher RR than those in the highest BMI quintile with respect to coronary heart disease (2.5 and 1.6, respectively) (Figure 4) and other cardiovascular diseases (1.7 and 0.89, respectively) (21). Even metabolic characteristics, such as plasma insulin concentration, have shown low to high gradient increases with corresponding increases in WHR. These responses were independent of BMI (although WHR group comparison was only performed in obese subjects) (Figure 5) (18).

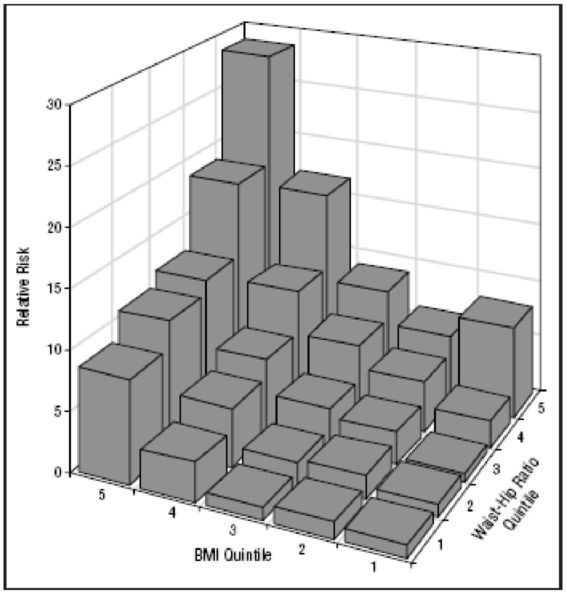

FIGURE 3: Age-adjusted relative risk of incident diabetes based on quintiles of BMI and WHR (21).

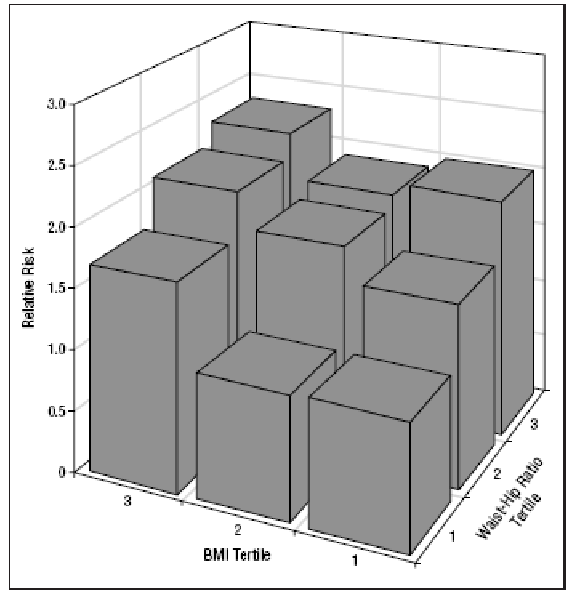

FIGURE 4: Age-adjusted relative risk of coronary heart disease-related mortality among never smokers based on tertiles of BMI and WHR (21).

Unfortunately, the association between disease risk and both BMI and WHR has been primarily determined for on overweight or obese patients. Too often, normal-weight individuals present with at-risk metabolic characteristics that go undetected due to their “healthy” body weight classification. Karelis et al. (31) and De Lorenzo et al. (15,16) have discussed subsets of obesity that are not widely understood: (a) metabolically healthy, but obese (MHO), (b) metabolically obese, but normal weight (MONW), and (c) normal-weight obese (NWO). Characteristics of each subset are listed in Table 5. The two more concerning subsets are those involving normal weight individuals. These individuals are less likely to receive early detection and treatment needed to prevent obesity-related diseases.

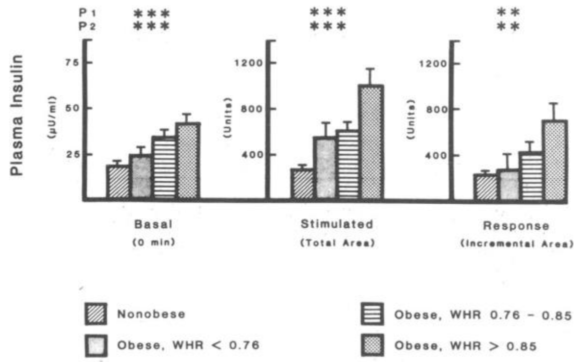

FIGURE 5: Relationship of plasma insulin to WHR (18).

Individuals in the MONW classification present with a normal BMI (18.5-24.9 kg·m^{-2}), fat mass greater than 30%, signs of insulin resistance, hyperinsulinemia, dyslipidemia, and are typically young (31). It is estimated that between 13-18% of the general population fall into this subset of obesity (31). The NWO individuals also present with a normal BMI (18.5-24.9 kg·m^{-2}), fat mass greater than 30%, and lower percent fat-free mass when compared to the general population of normal-weight individuals (16). However, unlike MONW, NWO individuals have few metabolic abnormalities associated with diabetes, thus do not have metabolic syndrome (16).

Despite there not being many significant anthropometric differences between normal-weight, NWO, and pre-obese individuals, a slight upward trend across categories does exist in the WHR (0.72, 0.76, 0.78, respectively) and separate waist and hip circumferences (15). Significant increases do occur across all three groups with respect to percent fat mass, with the normal-weight group having the lowest percent. Other significant increases are also found between the NWO and pre-obese groups when comparing fat mass, weight, and waist and hip circumferences, while a significant decrease is found between these two groups when comparing lean mass (15). These anthropometric differences place NWO women intermediate between normal-weight and pre-obese females. However, the metabolic profile of NWO women do not differ from normal-weight individuals. This indicates that anthropometric measures, and not a plasma lipid-lipoprotein profile, could be better indicators for obesity-related disease risk in this subset (16).

TABLE 5: Metabolic characteristics of obese subsets

Metabolically Healthy Obese (MHO) (31)	Metabolically Obese Normal Weight (MONW) (31)	Normal-Weight Obese (NWO) (15,16)
Low visceral fat	High visceral fat	Normal BMI
High BMI	Normal BMI	High fat mass
High fat mass	High fat mass	High TC/HDL cholesterol
High insulin sensitivity	Low lean body mass	High LDL/HDL cholesterol
Elevated HDL cholesterol	Low insulin sensitivity	Low TG/HDL cholesterol
Low Triglycerides	High liver fat	Normal blood glucose
	High Triglycerides	

HDL: high-density lipoproteins; LDL: low-density lipoproteins; TC: total cholesterol; and TG: triglycerides.

It is also believed that anthropometric measures such as body composition and RFD are related to the metabolic complications in MONW. Unlike NWO, MONW women present with metabolic abnormalities similar to those found in obese individuals. The MONW females have elevated total fat mass, body fat percentage, subcutaneous fat, and visceral fat compared to their metabolically healthy counterparts, yet have a similar BMI, body mass, and fat-free mass (31).

The characteristics of these new subsets of obesity suggest that anthropometric measures, particularly those involving visceral and subcutaneous fat mass, are critical in helping to identify those normal weight individuals with obesity-related risk factors. The goal then, was to determine which of the RFD measures were the best indicators of obesity-related disease risk factors regardless of the level of obesity.

2.2 STRONGEST ANTHROPOMETRIC PREDICTORS FOR DISEASE

2.2.1 Importance of WHR and RFD

Several anthropometric measures help determine body type. However, many of these measures are impractical to perform in a home or fitness center setting and require special personnel and equipment (such as magnetic resonance imaging (MRI) and computed tomography (CT)). Other methods, such as BMI, WHR, and waist circumference, may not correlate as well with visceral or subcutaneous adipose tissue when compared to tests such as CT topography, yet they still provide strong correlations with CVD and diabetes.

Depending on the study, population used, and data adjustments to control for co-variates, both WHR (8,14,51,55) and waist circumference (11,57) have been shown to be the strongest predictors of obesity-related disease risk. Other studies, however, indicate there is a negligible difference between the two in prediction strength (13,21,39,59). Never-the-less, both are usually used rather than BMI for prediction of diseases such as diabetes and CVD. Thus, the conundrum of which method is the most suitable remains.

Due to a higher rate of metabolic activity in visceral tissue the comparatively easy to use waist circumference is currently the method of choice for many practitioners. However, one of the main differences between male and female body types based on fat distribution lies in the hip circumference. Despite the common knowledge that women are typically smaller in stature than males, female hip circumference tends to be significantly larger (49,51). This larger hip circumference has been associated with lower risk of obesity-related diseases.

Lissner et al. (40) found that hip circumference in females is an independent and inverse risk estimator for myocardial infarction (MI) and CVD morbidity and mortality and diabetes morbidity (Table 6). This study showed a decreasing trend in RR from the lowest hip circumference quartile to the highest. In fact, hip circumference was found to be a statistically stronger predictor than waist circumference for all the endpoints examined.

Hip circumference has also been found to be inversely correlated with disease related metabolic risk factors, and positively correlated with healthy metabolic factors. Negative associations have been determined between hip circumference and triacylglycerols, insulin concentrations, visceral fat, subcutaneous abdominal fat, and both fasting and post-load glucose concentrations (49,51). Positive correlations have also been determined between hip circumference and HDL cholesterol (49).

TABLE 6: Relative risk values associated with hip circumference as a predictor of 24-year mortality and morbidity endpoints in Swedish women 38-60 years of age (40).

Quartile[a]	MI mortality	MI morbidity	CVD Mortality	CVD Morbidity	Diabetes Morbidity
Hip Q1	1 (reference)	1 (reference)	1 (reference)	1 (reference)	1 (reference)
Hip Q2	0.41	0.59	0.61	0.76	0.41
Hip Q3	0.47	0.56	0.44	0.76	0.57
Hip Q4	0.18	0.34	0.30	0.43	0.31

[a] Hip quartile cut-points at 94.5, 98.5, and 103.5 cm. Relative risk values adjusted for age, smoking status, BMI, and waist circumference at baseline.

With studies supporting the apparent protective power of hip circumference, especially among women, WHR becomes the method of choice in determining disease risk. This conclusion is further supported by a recent meta-analysis’s findings that a 1 cm increase in waist circumference only shows a 2% increase in the risk of CVD, whereas a 0.01 increase in WHR is associated with a 5% increase in risk (14). This indicates that WHR is a more sensitive marker than waist circumference in predicting disease risk. Before the final determination of the most effective RFD method, WHR must first be shown to be a strong predictor of disease-risk independent of obesity.

2.2.2 WHR as a predictor of disease risk independent of obesity

While BMI and WHR share many of the same properties, and consistently overlap when assessing disease-risk status, statistical applications can be used to separate the two anthropometric measures and test for the independent predictive effect of each. Several studies have shown that WHR even after adjustment for BMI still remains a strong factor for predicting diabetes or CVD (11,21,25,37,47,51). It is of note that age also failed to show significant correlations to WHR (36).

WHR has only shown low to moderate correlations with BMI (r = 0.28 to 0.56), as compared to the high correlations seen between waist circumference and BMI (r = 0.81 to 0.95) (11,25,47,49). The independent predictive power of WHR is important, as it allows disease-risk to be assessed separate of obesity status. The same does not hold true for waist circumference where it has such a high correlation with BMI. Establishing that WHR is mostly independent of BMI (no measure of obesity will truly be independent of another obesity variable), allows its use in this development of a body type classification system.

2.3 RATIONALE UNDERLYING DEVELOPMENT OF RFD CLASSIFICATION SYSTEM

2.3.1 Development of previous RFD classification systems

Vague (53) developed the first RFD classification system in the mid 1950's termed the "index of masculine differentiation (IMD)". This classification system was based on a ratio of the nape to sacrum ratio and the brachio-femoral ratio (skinfold thickness measured from behind the neck and at the attachment points of the four limbs). The scale ranged from < -75 to > 15, with women typically falling between -60 and 0, although extremes were found outside these two points (Figure 6).

IMD scale	Group
> +15	hyperandroid
+15	
0	android
−15	
	intermediate
−45	
60	gynoid
−75	
< −75	hypergynoid

FIGURE 6: Classification of masculine differentiation based on the index of masculine differentiation (IMD) scale (53).

Vague's classification system originated the terms "android" and "gynoid" (53). Vague defined gynoid and hypergynoid individuals by the comparatively larger amount of localized fat on the lower part of the body, poor muscule development, reduced arterial circulation activity and function, a normal basal metabolism, a moderate appetite and digestion, water retention, and insufficient venous circulation (53). Android and hyperandroid individuals were characterized by the exact opposite of the aforementioned types, with an increased amount of localized upper body fat, greater muscule development, “strong arterial circulation” (bordering on hypertension), a large appetite, normal basal metabolism, and normal venous circulation (53). Since these terms were first defined, several of the characteristics first believed to be associated with each type have been disproved (i.e. poor venous circulation and water retention associated with gynoid body type).

In 1978, Ashwell et al. (4) created another RFD classification scale based on waist and thigh diameters. This study borrowed its methodology from Stalley and Garrow’s somatotype photographic technique. Full body photographs were taken from the side, then outlines of the subjects were drawn on cellophane paper (Figure 7). These outlines were used to determine the waist and thigh diameters. The diameters were also rated visually by three observers. The results from the measured diameters were compared against the visual ratings. This procedure used a discriminate analysis which resulted in a final fat distribution score of $26\log_{10}(\text{waist diameter}\cdot\text{thigh diameter}^{-1})$. A later study performed by the same investigators changed this fat distribution score to $29\log_{10}(\text{waist circumference}) – 36\log_{10}(\text{thigh circumference}) + 10.5$. This new fat distribution score used circumferences in place of diameters, included an additional outline of the front-view of subjects (Figure 8), and a changed the classification names to “central” and “peripheral” (5).

More recently, Kirchengast et al. (32) constructed a fat distribution index involving a simple ratio of upper body fat to lower body fat. Regional body fat (g) was obtained using DXA, currently the only gold standard method with the capability to determine RFD. The study divided the subjects into one of three categories: gynoid (< 0.9), intermediate (0.9 – 1.1), or android (>

1.1) based on the RFD ratio. This method is fairly similar to the WHR except additional upper body and lower body fat deposits are taken into account as opposed to just measuring fat around the waist and hips. In this procedure, the upper body region ranged from below the chin to the hip joints, while the lower body region was inclusive of the body region below the hip joints.

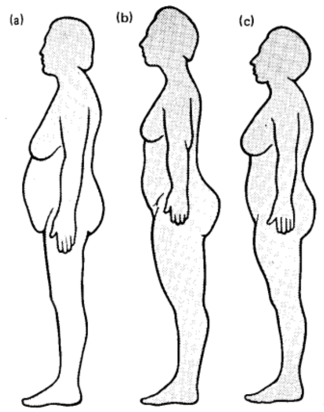

FIGURE 7: Guideline outlines used for subjective assessment of female body type, where (a) android, (b) gynoid, (c) intermediate (4).

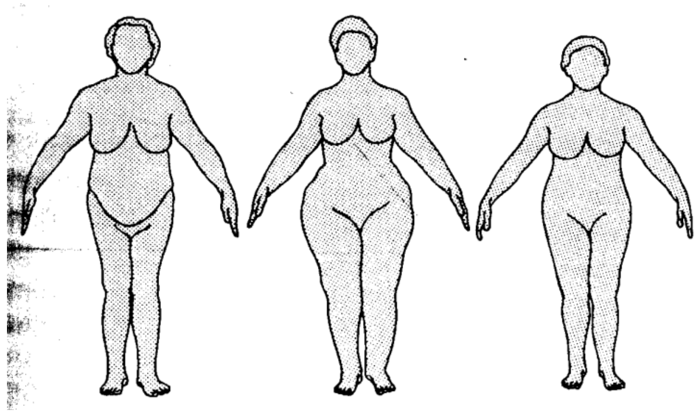

FIGURE 8: Guideline outlines used for subjective assessment of female body type, where (a) central, (b) peripheral, (c) intermediate (5).

Even though these three RFD assessment systems vary widely in their methodology, they still provide insight into the construction of a body type classification system. Vague's study (53) gives rise to the classification naming scheme, although the definitions have changed over time. Ashwell et al. (4,5) demonstrated through a discriminate analysis that visual identification of a body type can be relatively accurate, although objective measurements (diameters or circumferences) are more consistent and reproducible. Kirchengast et al. (32) created the simplest RFD equation, although it is based on an expensive and not readily accessible measurement technique. Also of great importance, both Vague (53) and Kirchengast et al. (32)

indicated that RFD is measured on a continuum and specific sub-classifications cannot easily be distinguished near their respective cut-points.

2.3.2 Evidence that body type falls along a continuum

Vague (53) demonstrated that body type subsets distribute along a continuum by assigning cut-points in 30 unit increments (based on a ± 15 standard deviation). The gynoid subgroup ranged from -75 to -45, the intermediate subgroup from -45 to -15, and the android subgroup from -15 to +15 (Figure 6). Kirchengast et al. (32) simply used 1.0 as the cut-point for delineating between android and gynoid, with a 0.1 buffer for the intermediate group (0.9 – 1.1). Those individuals < 0.9 were considered gynoid, and those > 1.1 were considered android.

Support for a continuum-based classification system is also found in the literature investigating the association between WHR and obesity-related disease-risk. When relative risk is divided into subgroups of increasing WHR, a clear and persistent increasing trend emerges (Tables 7 and 8). This gradual increase in disease-risk with a progression of WHR shows that although the relative risk for mid-range WHR groups is less than the highest WHR group, the relative risk is still higher than the lowest WHR group.

TABLE 7: Increasing relative risk trend across WHR subgroups (Quintiles).

		Quintiles				
Reference		**1**	**2**	**3**	**4**	**5**
Folsom (21)	Diabetes	1.0	1.9	3.0	6.0	11.5
	CHD[a]	1.0	1.3	1.6	2.3	2.5
	Other CVD	1.0	1.2	1.2	1.2	1.7
	Hypertension	1.0	1.1	1.4	1.7	2.2

[a] Coronary Heart Disease

TABLE 8: Increasing relative risk trend across WHR subgroups (0.04 Subgroups).

		< 0.72	0.72 – <0.76	0.76 - <0.80	0.80 – <0.84	0.84 - <0.88	≥0.88
Rexrode (47)	CHD[a]	1.00	1.50	2.02	2.02	2.28	2.43
Carey (11)	Diabetes	1.0	1.0	1.9	2.9	3.1	3.3

[a] Coronary Heart Disease

The MONW and NWO subgroups described by Karelis et al. (31) and De Lorenzo et al. (15,16) also indicate that obesity-related metabolic characteristics and fat mass patterns can be seen in normal weight individuals. The characteristics of these two groups place them between healthy normal weight individuals and pre-obese obese and obese individuals. This indicates once again, that disease-risk has a gradual increase between body type subgroups and maybe not be as closely tied to general obesity as once was thought.

2.3.3 Benefit of statistical clustering analysis

In most studies, when WHR, waist circumference, or BMI are used to assess disease-risk, cut-points are either arbitrarily determined by investigators or based on previously established recommendations from the literature. Cut-points for WHR sub-groups are usually subdivided by percentiles (such as quartiles or quintiles), literature values, or simple mathematical division of the number of subjects or independent variable range (Tables 1 and 2). In the literature, 0.80 is a common figure used to distinguish between gynoid and android subjects (54), while 0.86 or above is considered very high risk for obesity-related diseases (1).

Although many studies reference these cut-points, and some evidence exists to support them, most subgrouping originates arbitrarily – defined solely by mathematical manipulation of the subjects' characteristics. These divisions can be based on percentiles, equally sized groups, or simply a mean or median value. Few studies attempted to categorize subjects based on the RFD data itself. Ashwell et al. (4,5) used a standard linear-discriminant analysis to separate subjects into proposed gynoid, intermediate, and android groups after converting the measurements to logarithmic values. This method allowed for a separation between clusters of subjects and the development of an equation to predict a fat distribution score.

Newell-Morris et al. (45) also used a statistical clustering analysis to separate subjects according to various skinfold thickness. This study utilized a k-means clustering analysis that places subjects into a pre-determined number of subgroups. While the number of subgroups may be chosen *a priori*, the cut-points and number of subjects in each group are not. Four clusters were derived from the data set: one distinct gynoid group, one excessively android group, and two intermediate groups with android characteristics (all subjects were male).

Even though the statistical methods used by these two studies arbitrarily choose the number of subgroups, they show that clustering subjects according to fat patterning is possible. A statistical method such as a TwoStep clustering analysis allowed clustering of subjects according to RFD without a pre-determined number of subgroups. The removal of any investigator-chosen cut-points or number of subgroups allowed the data to cluster naturally into any number of subsets with varying amounts of subjects in each.

2.3.4 Regional fat prediction equations

Despite DXA being the gold standard to measure RFD, the instrument is expensive and non-accessible to the general population. Thus, it is efficient to use statistical equations whose predictor variables are strongly correlated with DXA measurements to develop an RFD classification system that is widely available and simple to use. Ritchie and Davidson (48) provide such equations specific for regional body sites (Table 9).

TABLE 9: Regional body fat equations (48).

Body Region	Regional fat mass (g) prediction equation (A: Circumference; B: BMI)	Multiple Regression Adjusted R^2
Waist	y = -7716.2 + 69.439*A + 235.28*B	0.8041
Hips	y = -13285 + 132.63*A + 221.32*B	0.8245

Where A: Circumference (cm), B: BMI (kg/m^2)

Using these equations in a simple RFD-ratio (RFD-ratio = Waist fat mass/Hip fat mass) allowed for comparison of statistically derived subgroup cut-points compared against similar cut-points based on the WHR. While the equations derived from DXA measurements may give a more accurate measure of actual fat mass in grams, WHR still remains an easier and more widely known method. The end goal of the present investigation is to assess the natural cut-points along a body type continuum using the most accessible method possible.

2.3.5 Inclusion/Exclusion rationale

In order to define the natural cut-points of female body types along a continuum, it was pertinent that the subject pool be as homogeneous as possible to provide strong internal validity. In previous studies, variations in age, menopausal status, parity status, smoking status, ethnicity, and disease state have created large cut-point standard deviations and confounding interpretations regarding body type continua. Eliminating these variables from a prediction equation resulted in a reduced ability to generalize; however, the natural cut-points most likely change with alterations to each variable.

2.3.5.1 Age As age increases in females, fat distribution has been shown to shift from predominantly gynoid to a more android localization. Kirchengast et al. (32) defined a fat distribution score as the upper body fat (g) divided by the lower body fat (g). Kirchengast et al. (32) showed an increasing trend in fat distribution scores with increasing age. Females 18-29 years old had a fat distribution score of 0.7 ± 0.4, while those 30-39 years had a score of 0.9 ± 0.4. This fat distribution score increased to 1.1 ± 0.4 and 1.5 ± 0.5 as age rose to 40-49 years and 50-65 years, respectively. Age was weakly correlated to WHR (r = 0.20), indicating that these two measures are independent of each other (36).

2.3.5.2 Menopausal status While closely linked to age, menopausal status was also important to consider when developing RFD equations. This was because hormonal factors that occur during this period cause a shift in anatomical localization of fat mass. Pre-menopausal females have been shown to have a fat distribution score of 0.7 ± 0.4, which increases to 1.1 ± 0.5 during menopause and 1.6 ± 0.5 post-menopause (32). WHR and menopause also have a weak correlation (r = 0.044) (36).

2.3.5.3 Parity status Parity status may also have an effect on RFD through a decrease in hip and thigh circumference and an increase in waist circumference with each birth (38). This is most likely due to the increase in mobilization of femoral fat during the lactation period (10). Parity is also weakly associated with WHR (r = 0.027) (36).

2.3.5.4 Smoking Caan et al. (9) found that smokers consistently have larger WHRs than non-smokers, and those subjects who stop smoking and lose weight have smaller mean changes in waist and hip circumferences than non-smokers.

2.3.5.5 Ethnicity Asian-Indian and Japanese women tend to have higher truncal and abdominal fat mass compared to Caucasians, while African-American women have lower visceral fat mass (23, 41). Although Caucasians and African-Americans have a similar WHR when matched for BMI, fasting insulin levels were significantly higher in African-American women while triglycerides were higher in Caucasians (41).

2.3.5.6 Disease status and medications Certain diseases, such as polycystic ovary syndrome (33), Cushing's syndrome (7), and HIV-associated lipodystrophy syndrome (46), can influence the body's metabolic and hormonal processes, altering the normal fat distribution pattern. Many medications may have the same effect, particularly certain psychotropic drugs, weight loss drugs, and steroids. Although these diseases and medications are quite common, it was important to employ subjects who were medically healthy and physically functional in order to increase internal validity of body type classification systems.

2.4 OTHER USE FOR STUDY FINDINGS

2.4.1 Weight loss

It was expected that another important application of the present investigation would involve assessing various body types to determine differences in the rate and effect of weight loss interventions. Currently, the effect of weight loss on fat distribution is not completely clear. Some studies claim that RFD remains constant despite a significant change in body weight (9), while others have found that comparatively larger changes occurred in the waist circumference than hip circumference during weight loss, indicating a decrease in WHR (4,54).

Several short-term weight loss studies have noted that those females with android fat distribution tend to lose more weight during interventions than females with gynoid fat distribution (22,29). Other studies have shown that long-term weight loss produces greater decreases in waist circumference than in hip or thigh circumferences (4,54). Despite these findings, it has been noted that RFD is not a useful prognostic indicator of a person's ability to lose weight (54). Based on the knowledge that gluetal-femoral fat depots have a lower lipolytic rate than abdominal cells, it is plausible that different body types may affect the rate at which weight loss occurs while not hindering the overall ability to reduce body mass through interventions.

2.5 SUMMARY

Based on the data found in the literature review, it has been determined that data-derived cut-points do not exist for females along continua based on either WHR or RFD-ratio. The literature has also shown that disease-risk is strongly correlated with obesity-related diseases such as coronary heart disease and diabetes. It was also found that certain normal-weight individuals possess metabolic and circulatory-related characteristics similar to those found in overweight or obese females, thus these individuals must be included with equal importance. Using the literature, it was determined that WHR provides a greater benefit for use in developing a body type continuum than does WC. Finally, review of the literature provided an insight into previous developments of body fat classification systems and the pros and cons of each method.

This assessment of the literature found support for the concept and development of the current investigation.

3.0 METHODS

3.1 SUBJECTS

This investigation included 73, 18-29 year old, pre-menopausal, Caucasian females. Potential subjects were included if they were:

1. Nulliparious
2. Non-smokers
3. Not taking medications that would effect regional fat distribution
4. Do not have any endocrine, cardiovascular, or metabolic diseases
5. At any level of physical fitness and perform any range of aerobic physical activity throughout the day, and who are presently or have been athletes
6. Not currently undergoing any weight loss regimen

Potential subjects were excluded from this study based on the following criteria:

1. Taking any psychotropic medications that could change the metabolic rate of adipose tissue such as:
    a. Tricyclic antidepressants, i.e. Amitriptyline (Elavil) or Imipramine (Tofranil).
    b. Serotonin-specific reuptake inhibitors such as Paroxetine (Paxil), Sertraline (Zoloft), or Fluoxetine (Prozac).
    c. Dopamine reuptake inhibitors such as Bupropion (Wellbutrin).

2. Taking any weight-loss specific medications such as:
    a. Phentermine (Fastin).
    b. Orlistat (Alli, Xenical).
    c. Sibutramine (Meridia).
    d. Diethylpropion (Tenuate).
    e. Benzphetamine (Didrex).
    f. Phendimetrazine (Bontril).
3. Diagnosed with diabetes mellitus, metabolic syndrome, chronic heart failure, any endocrine disorder, or lipodystrophy syndrome (HIV-associated).
4. Taking other metabolic altering medications such as:
    a. Metformin.
    b. Oral steroids such as prednisone within the past six months.
    c. Medication with diuretic properties.
5. Have undergone gastric bypass or lap band surgery.
6. Are currently pregnant, or have previously had children.

Subjects wore light exercise clothing, such as a cotton tee shirt and exercise shorts. Swimwear with no excessive embellishments (i.e. ruffles, buckles, or multiple layers of fabric) was permitted in lieu of undergarments. Shoes were removed for height and weight measurements. A bioelectrical impedance analysis (BIA) was used to measure total body fat and lean tissue. BIA measures the differential speed of an electrical current as it passes through fat and lean tissue and is influenced by the water content of these two tissue types. As such, subjects must be properly hydrated to ensure a correct measurement of body fat (%). Proper hydration included: abstaining from alcohol consumption for the previous 48 hours, as well as not consuming any products with diuretic properties (i.e. caffeine) for the previous 24 hours (2). Subjects also refrained from any exercise for twelve hours prior to the assessments, and eating or drinking four hours prior to the assessments (2). The bladder was voided 30 minutes before the start of any measurements.

Each subject signed an informed consent prior to participation, as well as completed a medical history form. Subjects were recruited from the University of Pittsburgh's Oakland campus through the use of posted flyers. Kirchengast et al. (32) found that 15.1% of women (aged 18-29 years) fell into the android classification, while 72.2% of women (aged 18-29 years) were classified as gynoid. Initially, 100 females were to be recruited for the present investigation. However, due to difficulty recruiting overweight and obese females, only 73 subjects underwent measurement testing. After 73 subjects were tested, data were checked to ensure that at least fifteen percent of the subjects had a WHR above 0.8 (1,32) and at least fifty percent of the subjects had a WHR below 0.8 (1,13,32). These percentages were not met, however, further recruitment effort directed at higher BMI individuals did not increase the percentage of individuals with a WHR greater than 0.8. All procedures were approved by the University of Pittsburgh's Institutional Review Board for human subject experimentation.

3.2 RESEARCH DESIGN

This investigation used a within subject cross-sectional design to construct separate continua for female body types based on WHR and predicted RFD-ratio. Separate TwoStep statistical clustering analyses were used to indentify body type classifications based on a WHR continuum and a RFD-ratio continuum.

Upon voluntary agreement to enter the study, subjects signed a consent form to participate followed by a physical activity questionnaire (Appendix) and an anthropometric assessment. Measurements were performed in individual fifteen-minute blocks by the same investigator.

3.3 VARIABLES

3.3.1 Predictor variables

Body type is defined as the combination of body shape and body fat distribution. *Body type* was statistically determined by separately clustering WHR data and predicted regional fat distribution data.

It was expected that four body types existed for females: *hyper-gynoid*, *gynoid*, *android*, and *hyper-android* (Figure 9). A common delineation between gynoid and android females is 0.8 (54).

- *Hyper-gynoid*: females with an excessive amount of fat in the hips and buttocks as compared to the amount of fat in the abdominal area.
- *Gynoid:* females with predominantly more fat in the hips and buttocks as opposed to the abdominal area. However, the ratio of upper body fat to lower body fat is higher than *hyper-gynoid* females.
- *Android:* females with more adipose tissue in the abdominal region than in the lower body.

- *Hyper-android:* females with an excessive amount of fat in the abdominal area as opposed to the lower body. The fat distribution ratio is the highest of the four body types.

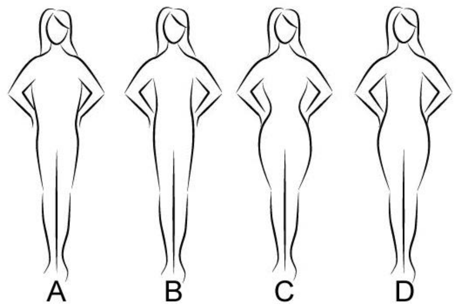

FIGURE 9: Proposed body types – A: hyper-android, B: android, C: gynoid, and D: hyper-gynoid (19).

3.3.2 Criterion variables

WHR and *fat distribution* were determined for each subject.

WHR was determined by dividing the waist circumference by the hip circumference. *Fat distribution* was predicted using the waist and hip regional body fat equations for college-aged Caucasian females (48). The predicted waist fat mass was then divided by the predicted hip fat mass forming a regional fat distribution ratio. The equations employed the following: waist circumference (cm), height (m), weight (kg), and BMI ($kg \cdot m^{-2}$).

3.4 ANTHROPOMETRIC MEASUREMENTS

Anthropometric measurements for computation of WHR was obtained using procedures described in *the Guidelines for Graded Exercise Testing and Prescription* by the American

College of Sport Medicine (1). Anthropometric measurements for the RFD prediction equations were obtained following procedures from Ritchie and Davidson (48). All measurements were taken by a single, well-trained technician.

3.4.1 Body circumferences

Duplicate circumference measurements were taken to the nearest 5 mm using a flexible, inelastic tape. Measurements were repeated if the duplicate values were greater than 5 mm apart (1,2). The waist circumference was measured first, the abdomen circumference second, and the hip circumference third. Measurements were repeated using the same procedures and site sequence. A minimum of one minute separated the original and duplicate measurements.

All measurements were taken with the tape horizontal to the floor, with the investigator inspecting visually from the front and the side. Two marks were made with a felt tip marker along the top of the measuring tape, one on the left and one on the right side, to denote the level of the tape during the first measurement. Abdomen and waist circumferences were taken with the tape directly on the skin, while hip circumferences were taken with the tape on no more than one light layer of clothing (i.e. undergarments or swimsuit). The circumference measurement procedures are outlined below:

- *Abdomen circumference*: A horizontal measurement was taken at the level of the umbilicus with the subject standing and muscles relaxed. This measurement was used in the equation to predict fat distribution.
- *Hip circumference*: A horizontal measurement was taken at the largest circumference of the buttocks/hips with the subject standing upright and feet together. During the first hip circumference measurement, the tape was placed around the area determined visually to

be the largest, then slid up and down in 5 cm adjustments from this location until the actual largest area was determined.

- *Waist circumference*: A horizontal measurement was taken at the narrowest part of the torso, between the umbilicus and xiphoid processes. The subject stood erect with arms at the side, feet together, and abdomen relaxed. During the first waist circumference measurement, the tape was placed around the area determined visually to be the narrowest, then slid up and down in 5 cm adjustments from this location until the actual smallest area was determined. This measurement was used to determine WHR.

3.4.2 Body weight, height, and composition

Shoes and socks were removed for all body composition measurements. Body weight (kg) was determined using a DetectMedic Scale (Detecto Scales Inc., New York). Height (cm) was measured using a DetectMedic Scale and attached standiometer (Detecto Scales Inc., New York). Subjects stood erect with feet flat on the floor, looking straight ahead with the head in a neutral position. Arms were placed by the side and relaxed. Bioelectrical impedance analysis (BIA) was used to determine subjects' percent body fat using the standard setting on a Tanita TBF-300A BIA scale (Tanita, Arlington Heights, IL). BMI was calculated as follows:

$$BMI\,(kg \cdot m^{-2}) = \frac{Weight(kg)}{Height(m)^2}.$$

3.4.3 Regional body fat distribution equations

The regional body fat distribution equations employed for this study were derived from Ritchie and Davidson (48), and were designed for use with college-aged Caucasian females. These equations use a combination of circumferences, BMI, and constants to estimate the fat mass (g) for a specified anatomical region. The equations that were used for this study are shown in Table 9.

When compared to measurements from a DXA analysis of the same body area, the chest equation has a R^2=0.83, and the waist equation has a R^2=0.80, thus making them suitable for use in the current study.

3.5 STATISTICS

Descriptive data for anthropometric measurements (i.e. height, weight, BMI, percent body fat, aerobic physical activity level) were calculated as mean ± standard deviation (SD). Normality of data distribution was also tested. All analyses were performed using the Statistical Package for the Social Sciences (SPSS, version 20.0, Chicago, Ill., USA). Statistical significance will be set at an alpha $\leq$0.05 for all analyses.

The presence of data clusters along the WHR continuum and RFD-ratio continuum were examined using a TwoStep clustering analysis. A TwoStep clustering analysis produces solutions based on continuous or categorical variables without the need to specify a predetermined number of clusters. This analysis can use the input of only one variable (WHR or RFD-ratio) per subject for clustering purposes. From the output, each cluster's mean and SD is determined along with data cut-points delineating the borders of each cluster. The number of subjects that fall into each cluster is also presented in the analysis. In addition, a secondary TwoStep analysis was also employed to examine clustering using BMI plus WHR and BMI plus RFD-ratio. A comparison of descriptive data [aerobic physical activity (minutes/week), body fat (%), and fat mass (g)] between clusters was performed using a one factor ANOVA.

If both the WHR and RFD-ratio methods yielded the same number of body type clusters, a follow-up objective of this investigation was to compare the two methodologies to determine if they could be used interchangeably. In order to perform this comparison, a one factor ANOVA would separately analyze WHR and RFD-ratio data to determine if the clusters were significantly different. Following this, a correlation and regression analysis with the same data (i.e. WHR only, RFD-ratio only, BMI plus WHR, and BMI plus RFD-ratio) was employed to determine if using the methodology from one body type continuum could place a subject into the corresponding cluster formed on the other continuum. Such a finding could allow either method to be used to determine body type for young adult females.

4.0 RESULTS

This investigation examined the "natural" clustering of body types for healthy females aged 18-29 years old. A within subject cross-sectional design was used to construct separate continua for female body types based on WHR and predicted RFD-ratio where BMI was and was not included in the calculation. WHR was determined by measuring the waist circumference at the narrowest part of the torso, between the umbilicus and xiphoid processes. The hip circumference measurement was taken around the largest part of the buttocks/hips. Anthropometric measurements were taken with the subject standing upright and feet together. The waist circumference was then divided by the hip circumference to produce a ratio. The RFD-ratio was determined by measuring the hips as above and the abdomen circumference at the level of the umbilicus. These values were inserted into the RFD equations in Table 9. The value derived from the "waist" equation was divided by the value from the "hip" equation to construct a ratio.

Once the two ratios were determined for each subject, a TwoStep statistical clustering analysis was used to indentify body type classifications based on either a WHR continuum or a RFD-ratio continuum. These calculations were conducted with and without the inclusion of BMI. From there, a one factor ANOVA was used to determine if the body type clusters were significantly different from each other. If applicable, a correlation and regression analysis with the same data (i.e. WHR only, RFD-ratio only, BMI plus WHR, and BMI plus RFD-ratio) was then employed to determine if using the methodology from one body type continuum could place a subject into the same cluster formed on the other continuum.

4.1 DESCRIPTIVE INFORMATION

4.1.1 Subject descriptives

The investigation initially intended to recruit 100 Caucasian females aged 18-29 years with no known health conditions. Due to recruitment limitations in identifying high WHR females, seventy-three subjects actually underwent testing with no subjects removed from the final data set. Table 10 lists the mean ± SD for age, weight, height, BMI, body fat percentage, waist circumference, abdomen circumference, hip circumference, and aerobic physical activity level for the total group of 73 subjects.

Fifty-two of the subjects were considered under-weight or normal weight according to ACSM BMI standards (1), while 18 subjects were considered overweight, and three were considered obese. According to ACSM body fat percentage guidelines (1), seven subjects were at or above the 75^{th} percentile (lowest body fat percentage), 10 subjects were at or between the 50^{th} and 75^{th} percentiles, 22 subjects were at or between the 25^{th} and 50^{th} percentiles, and 34 subjects fell at or below the 25^{th} percentile.

TABLE 10: Subject descriptive information

Measurement	Mean	± SD
Age (years)	20.93	1.95
Weight (kg)	62.31	9.92
Height (cm)	163.78	6.70
BMI (kg/m^2)	23.19	3.21
Body Fat (%)	25.85	6.59
Waist Circumference (cm)	71.29	6.79
Abdomen Circumference (cm)	82.84	9.32
Hip Circumference (cm)	98.23	6.67
Physical Activity (min/week)	203.45	187.39

4.2 TWOSTEP CLUSTER ANALYSIS

The TwoStep cluster analysis produces solutions based on continuous or categorical variables. The calculation is conducted without the need to specify a predetermined number of clusters based on as little as one variable, thus making it suitable for use in this investigation. The TwoStep analysis was performed using the WHR and RFD-ratio separately.

4.2.1 WHR cluster analysis

A cluster analysis based on WHR alone showed that three good quality clusters were naturally formed in the subject subset that was studied (Figure 10). Cluster 1 contained 5 subjects with a mean WHR of 0.81 ± 0.03, Cluster 2 consisted of 34 subjects with a mean of 0.74 ± 0.01, and Cluster 3 had 34 subjects with a mean of 0.70 ± 0.02. Cutpoints between the clusters were determined by averaging the distance between the minimum cluster value of the larger ratio cluster and the maximum cluster value of the smaller ratio cluster. Cutpoint 1 (between Clusters 1 and 2) fell at a WHR of 0.78, while Cutpoint 2 (between Clusters 2 and 3) was found to be 0.72. Therefore, those subjects with a WHR > 0.78 were placed into Cluster 1, those with a WHR of 0.72 ≤ 0.78 were placed into Cluster 2, and subjects with a WHR < 0.72 were placed into Cluster 3.

4.2.2 RFD-ratio cluster analysis

A cluster analysis based on the RFD-ratio alone showed the formation of three good quality clusters. Cluster 1 contained 15 subjects with a mean RFD-ratio of 0.81 ± 0.03, Cluster 2 consisted of 35 subjects with a mean of 0.71 ± 0.03, and Cluster 3 had 23 subjects with a mean of 0.62 ± 0.05 (Figure 11). Cutpoint 1 (between Clusters 1 and 2) occurred at a RFD-ratio of 0.78, while Cutpoint 2 (between Clusters 2 and 3) occurred at 0.68. Subjects with a RFD-ratio > 0.78 were placed into Cluster 1, those with a RFD-ratio 0.68 ≤ 0.78 were placed into Cluster 2, and subjects with a RFD-ratio < 0.68 were placed into Cluster 3.

4.2.3 Cluster analyses with body mass index

As health problems and weight management plans can be influenced by a person's total weight regardless of fat distribution, including BMI as part of the cluster analysis can be beneficial. Pairing BMI with either WHR or RFD-ratio in the statistical cluster analysis produced only two good quality clusters, as compared to three when using WHR or RFD-ratio independently. The resulting clusters each had a mean ratio value as well as a mean BMI, but only one cutpoint (as there were only two clusters). The results are shown in Table 11.

TABLE 11: TwoStep Clustering results for WHR and RFD-Ratio in conjunction with BMI

	Cluster	N	Mean Ratio ± SD	Cutpoint between clusters
WHR with BMI	1	26	0.74 ± 0.04	0.73
	2	47	0.72 ± 0.03	
RFD-ratio with BMI	1	33	0.76 ± 0.06	0.74
	2	40	0.66 ± 0.06	

WHR: Waist-to-Hip Ratio; RFD-ratio: Regional Fat Distribution-Ratio.

4.3 CLUSTER COMPARISONS

Once clusters for both WHR and RFD-ratio were determined, it was then possible to examine differences in descriptive characteristics between the subjects in each cluster. Descriptive data, such as body fat percentage (%), regional fat mass (g), and aerobic physical activity level (min/wk), can help to explain the differences in body types as indicated by the ratios. Cluster comparisons were made using a One-Way ANOVA.

TABLE 12: Means ± SD for individual clusters based on body fat percentage

Cluster	WHR Mean ± SD	RFD-Ratio Mean ± SD
1	35.54 ± 6.0	29.45 ± 8.0
2	26.42 ± 5.9	26.83 ± 5.5
3	23.85 ± 6.1	22.00 ± 5.3

WHR: Waist-to-Hip Ratio; RFD-Ratio: Regional Fa Distributiotn-Ratio.

4.3.1 Body fat percentage cluster comparison

The means ± SD for each cluster within the WHR and RFD-ratio classification systems can be found in Table 12. A One-Way ANOVA for body fat percentage indicated that there were statistically significant differences between the clusters for both WHR and RFD-ratio (Table 13). Tukey’s honestly significant difference *post hoc* test was used to determine if the clusters were significantly different from each other. This *post hoc* test determines the minimum difference between the means of any two groups by not underestimating the least significant difference.

Tukey's *post hoc* test performed on the WHR clusters showed that Cluster 1 was significantly greater than Clusters 2 and 3, and that Clusters 2 and 3 were not significantly different from each other (Table 14). Tukey's *post hoc* analysis indicated that the RFD-ratio Clusters 1 and 2 were not significantly different, though Cluster 3 was significantly lower than Clusters 1 and 2 (Table 14).

TABLE 13: One-Way ANOVA of body fat percentage for Waist-to-Hip Ratio and Regional Fat Distribution-ratio clusters

		Sum of Squares	df	Mean Square	F	Significance	Eta^2
WHR Clusters	Between Groups	616.44	2	308.22	8.60	0.000	0.197
	Within Groups	2510.17	70	35.86			
	Total	3126.60	72				
RFD-Ratio Clusters	Between Groups	568.23	2	284.11	7.77	0.001	0.182
	Within Groups	2558.23	70	36.55			
	Total	3126.60	72				

WHR: Waist-to-Hip Ratio; RFD-ratio: Regional Fat Distribution-Ratio.

TABLE 14: Tukey *post hoc* analysis for Waist-to-Hip Ratio and Regional Fat Distribution-ratio clusters with body fat percentage as the dependent variable.

	Cluster	Cluster	Significance
WHR Clusters	1	2	0.006
	1	3	0.000
	2	3	0.188
RFD-ratio Clusters	1	2	0.342
	1	3	0.001
	2	3	0.011

WHR: Waist-to-Hip Ratio; RFD-ratio: Regional Fat Distribution-Ratio.

TABLE 15: Means ± SD for individual clusters based on regional and total body fat (g)

	Cluster	Abdomen Fat Mass Mean ± SD	Hip Fat Mass Mean ± SD	Total Fat Mass Mean ± SD
WHR Clusters	1	5526.02 ± 1968.29	6601.79 ± 2148.06	12127.80 ± 4107.42
	2	3630.60 ± 1157.82	4930.28 ± 1429.26	8560.87 ± 2567.33
	3	3053.85 ± 1159.27	4564.96 ± 1430.96	7618.81 ± 2574.27
RFD-Ratio Clusters	1	4527.67 ± 1678.25	5529.32 ± 1898.57	10056.98 ± 3571.68
	2	3627.71 ± 1099.35	5064.48 ± 1426.28	8692.19 ± 2519.94
	3	2609.41 ± 873.28	4158.71 ± 1217.55	6768.12 ± 2076.59

WHR: Waist-to-Hip Ratio; RFD-Ratio: Regional Fat Distribution-Ratio.

4.3.2 Regional and total fat mass cluster comparison

Means ± SD for each cluster within the two classification systems can be found in Table 15. Regional fat mass (g) was predicted for the abdominal and hip areas using the equations from Table 9. Total fat mass was calculated by adding the two areas. Separate One-Way ANOVA, using WHR and RFD-ratio as independent factors, indicated that the clusters within all three areas (abdomen, hips, and total) were significantly different from each other (Table 16).

Tukey’s *post hoc* analysis of the regional and total fat mass clusters as determined by the WHR can be found in Table 16. For the abdomen region and total fat mass Clusters 1 and 2 were found to be significantly different. Clusters 1 and 3 were significant across all three regions. Clusters 2 and 3 were not significantly different in all three regions.

The Tukey *post hoc* analysis for regional and total fat mass clusters based on RFD-ratio are also shown in Table 17. *Post hoc* testing of RFD-ratio “abdomen” clusters indicated that all three clusters were significantly different from each other. RFD-ratio “hip” clusters only showed significant differences between Clusters 1 and 3. Clusters 1 and 2 and Cluster 2 and 3 were not significantly different. The final regional and total fat mass *post hoc* test involving the RFD-ratio total clusters showed that Clusters 1 and 2 were not significantly different, though Clusters 1 and 3 and Clusters 2 and 3 were significantly different.

4.3.3 Aerobic physical activity level cluster comparison

Weekly aerobic physical activity level (min/week) was obtained through a short questionnaire (Appendix). If subjects reported a range for either number of days or minutes per session, the lower value was used for the cluster analysis. For the WHR clusters, the average minutes per week that subjects engaged in aerobic physical activity was 259.40 ± 251.10 for Cluster 1, 151.03 ± 118.74 for Cluster 2, and 247.65 ± 222.62 for Cluster 3. The aerobic physical activity levels within RFD-ratio clusters averaged 201.47 ± 175.61, 197.57 ± 179.40, and 213.70 ± 213.06 minutes per week for Clusters 1, 2, and 3, respectively. Regardless if WHR or RFD-ratio was used, there was no significant difference between any of the clusters.

TABLE 16: One-Way ANOVA for regional and total fat mass (g).

Cluster	Fat Mass		Sum of Squares	df	Mean Square	F	Significance	Eta^2
WHR	**Abdomen**	Between Groups	27866403.89	2	13933201.94	9.371	0.000	0.211
		Within Groups	104083205.87	70	1486902.94			
		Total	131949609.76	72				
	Hip	Between Groups	18281150.19	2	9140575.09	4.170	0.019	0.106
		Within Groups	153440472.74	70	2192006.75			
		Total	171721622.92	72				
	Total	Between Groups	91029130.16	2	45514565.08	6.325	0.003	0.153
		Within Groups	503679248.23	70	7195417.83			
		Total	594708378.39	72				
RFD-Ratio	**Abdomen**	Between Groups	34649798.80	2	17324899.40	12.47	0.000	0.263
		Within Groups	97299810.97	70	1389997.30			
		Total	131949609.76	72				
	Hip	Between Groups	19479197.87	2	9739598.93	4.48	0.015	0.113
		Within Groups	152242425.06	70	2174891.79			
		Total	171721622.92	72				
	Total	Between Groups	105339359.50	2	52669679.75	7.534	0.001	0.177
		Within Groups	489369018.89	70	6990985.98			
		Total	594708378.39	72				

WHR: Waist-to-Hip Ratio; RFD-ratio: Regional Fat Distribution-Ratio.

TABLE 17: Tukey *post hoc* examination of regional and total fat mass (g) between clusters based on Waist-to-Hip Ratio and Regional Fat Distribution-Ratio.

		Cluster	Cluster	Significance
WHR Clusters	Abdomen	1	2	0.005
		1	3	0.000
		2	3	0.132
	Hips	1	2	0.055
		1	3	0.015
		2	3	0.568
	Total	1	2	0.019
		1	3	0.002
		2	3	0.322
RFD-Ratio Clusters	Abdomen	1	2	0.041
		1	3	0.000
		2	3	0.005
	Hips	1	2	0.566
		1	3	0.018
		2	3	0.064
	Total	1	2	0.223
		1	3	0.001
		2	3	0.023

WHR: Waist-to-Hip Ratio; RFD-ratio: Regional Fat Distribution-Ratio.

4.4 INTERCHANGING WAIST-TO-HIP RATIO AND REGIONAL FAT DISTRIBUTUION RATIO

As a follow-up to the original purpose of the investigation, the ability to interchange one method to classify body type clusters with the other was examined. A One-Way ANOVA was used to determine if the body type clusters differed between the WHR and RFD-ratio methods (Table 16). It was intended that if the clusters were not significantly different a correlation and regression analysis would be performed. The R^2 value derived from these analyses would be used to determine if there was a strong enough correlation between the WHR and RFD-ratio to use them interchangeably. However, the ANOVA and Tukey *post hoc* tests showed that there was a significant difference between the two sets (i.e. WHR and RFD-ratio) of clusters (Tables 16 and 17, respectively), indicating that it was not possible to use the two body type classification systems interchangeably with this group of young adult women.

TABLE 18: One-Way ANOVA results comparing Waist-to-Hip Ratio and Regional Fat Distribution-Ratio.

	Sum of Squares	df	Mean Square	F	Significance	Eta^2
Between Groups	12.27	2	6.14	28.24	0.000	0.426
Within Groups	15.21	70	0.22			
Total	27.48	72				

TABLE 19: Tukey *post hoc* comparison of Waist-to-Hip Ratio and Regional Fat Distribution-Ratio clusters.

TwoStep Cluster Number	TwoStep Cluster Number	Mean Difference	Standard of Error	Significance
1	2	-0.76	0.14	0.000
	3	-1.16	0.16	0.000
2	1	0.76	0.14	0.000
	3	-0.40	0.13	0.006
3	1	1.16	0.16	0.000
	2	0.40	0.13	0.006

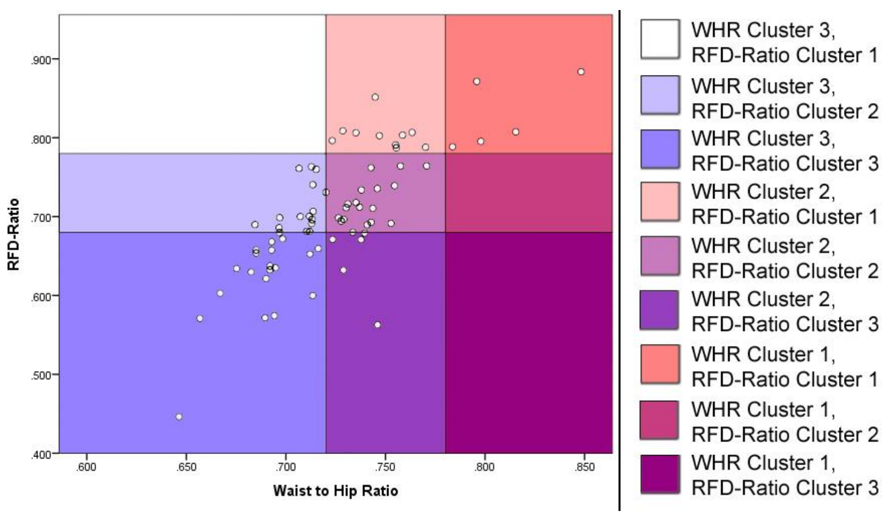

FIGURE 10: Correlation between Waist-to-Hip Ratio and Regional Fat Distribution-Ratio. Graph indicates cluster overlap between the two ratios. For each ratio, Cluster 1 includes those subjects with the highest ratio, while Cluster 3 includes those subjects with the lowest ratio.

4.5 SUMMARY

The study population used in this investigation included mostly normal-weight, college-aged females. Cluster analysis indicated that the subjects' body types could be grouped into three clusters regardless of whether a WHR or RFD-ratio method was used. The results also showed that while the clusters within each ratio type differed significantly based on body fat percentage, fat mass, or aerobic physical activity level, the comparatively small effect size indicated that these descriptive characteristics only had a weak effect. Finally, ANOVA showed that WHR and RFD-ratio could not be used interchangeably to place subjects into body type clusters.

5.0 DISCUSSION, CONCLUSIONS, AND RECOMMENDATIONS

The purpose of this investigation was to determine if two new female body type classification systems could be developed based on the WHR and RFD-ratio. It was proposed that subsequent to follow-on population based clinical studies, these classification systems could provide a more individualized, yet simple method of identifying those females who may be at risk for developing obesity-related diseases. Subjects used to develop the classification systems included normal-weight as well as overweight and obese adult females.

To develop the new body type classification systems, a TwoStep cluster analysis was employed. Using this analysis, three body type clusters were formed for the WHR classification system and three for the RFD-ratio classification system. This statistical method of subject separation allowed for a natural formation of body type clusters, rather than identifying groups formed *a priori* as has been the customary approach in published literature. Body type clusters were formed along a continuum for WHR and for RFD-ratio, as well as for WHR combined with BMI and RFD-ratio combined with BMI.

The initial experimental step determined body type clusters within each classification system. Descriptive data were then compared between clusters within a classification system. The intent was to determine if a specific descriptor differed significantly between body type clusters. Descriptors for this comparison were body fat percentage (%), regional fat mass (g), and aerobic physical activity level (min/wk). As a secondary purpose, a correlation was computed to determine if WHR and RFD-ratio systems were related and hence could be used interchangeably to classify female body types.

5.1 PRIMARY FINDINGS: BODY TYPE CLASSIFICATIONS USING WAIST-TO-HIP RATIO AND REGIONAL FAT DISTRIBUTION RATIO

5.1.1 TwoStep cluster analysis for WHR and RFD-Ratio

Waist-to-Hip Ratio was determined by dividing the circumference of the abdomen by the circumference of the hips. It was expected that four clusters (*hypergynoid, gynoid, android,* and *hyperandroid*) would naturally form for the female subjects that were studied. However, only the first three of these clusters emerged within each of the two classification systems when the TwoStep cluster analysis was performed.

The findings identified three rather than the four female body types that were projected in the hypothesis. This was likely due to difficulty recruiting subjects with a high WHR (typically overweight or obese individuals). The vast majority of subjects that volunteered to participate had a WHR less than 0.8. The TwoStep cluster analysis separated the subjects into three groups with WHR as follows: < 0.72, 0.72 to 0.78, and > 0.78. These cut-points indicate that *hypergynoid, gynoid,* and *android* body type groups formed along a continuum from low to high WHR. These cut-point ranges are similar to those found in previous literature for adult females (4,32,53). As noted, very few subjects had a WHR over 0.8; a cut-point typically used to delineate high disease-risk in individuals who have a *hyperandroid* body type classification.

Nevertheless, it is proposed that if a more robust recruitment of subjects in this higher WHR category had been possible, a fourth body type cluster (i.e. *hyperandroid*) may have emerged.

RFD-ratio was calculated by dividing abdominal fat mass by femoral fat mass as predicted using DXA-based equations from Ritchie and Davidson (48). It was expected that four female body type clusters (*hypergynoid, gynoid, android,* and *hyperandroid*) would naturally form through the use of a TwoStep cluster analysis. The TwoStep cluster analysis identified three good quality clusters with RFD-ratio's as follows: < 0.68 (*hypergynoid*), 0.68 to 0.78 (*gynoid*), and > 0.78 (*android*). As the same subjects were used to develop both the WHR and RFD-ratio clusters, it can be proposed that a *hyperandroid* group was not identified by the analysis due to lack of subjects with a high RFD-ratio.

A WHR of 0.80 is commonly used as the cut-point to delineate those individuals at high-risk for obesity-related diseases (1). However, the 0.80 WHR cut-point was originally chosen as a risk indicator because it fell at the midpoint of the group of subjects being studied (54). It was not based on actual documentation of disease risk or body type delineation at that particular ratio. The results of these previous investigations indicated that significant disease-risk differences existed between the high WHR and low WHR groups. Thus, a WHR of 0.80 was considered an effective cut-point for determination of clinical risk based on excess fat mass. In the present investigation, the TwoStep cluster analysis demonstrated that when data derived from healthy female subjects were allowed to cluster naturally according to body type, the WHR cut-point was 0.78. This cut-point separated the *gynoid* and *android* body types. It is possible that future research may show that this is also the cut-point that delineates those subjects at high risk for obesity-related diseases. In the present investigation, the TwoStep cluster analysis using the RFD-ratio identified a 0.78 cut-point between the *gynoid* and *android* groups. However, methodological differences exist between the present and previous investigations regarding how regional fat mass was calculated and defined. As such, it was not feasible to identify a standard cut-point that could be used for comparative purposes when interpreting the present findings.

5.1.2 TwoStep cluster analysis for WHR and RFD-Ratio with the addition of body mass index

Abundant experimental evidence demonstrates a correlation between an increase in body fat and disease-risk. Although the independence of WHR from BMI was previously discussed, the fact remains that those individuals with a higher BMI typically demonstrate comparatively more metabolic and cardiovascular diseases (3,25,34,35,37,39,56). Therefore, it was deemed appropriate to combine BMI with both the WHR and RFD-ratio data as part of the TwoStep analysis to examine possible contributory influences of standardized measures of adiposity on cluster distribution of female body types.

A TwoStep cluster analysis using both WHR and BMI as variables produced two good quality clusters. The cut-point between the two clusters fell at 0.73. A TwoStep cluster analysis using RFD-ratio and BMI also demonstrated two good quality clusters. A cut-point of 0.72 was found between these two clusters. Cut-points for both the WHR+BMI and RFD-ratio+BMI systems were determined by calculating the average of the highest ratio from one cluster and the lowest of the next. As was noted for the classification systems based on WHR and RFD-ratio alone, it is unknown if a comparatively more heterogeneous sample size with regard to body fat mass would increase the number of clusters identified in the female sample that was studied.

However, upon closer inspection of the cluster analysis with respect to predictor importance, it was found that BMI vastly overwhelmed the WHR and RFD-ratio for body type differentiation. The importance level of BMI was 1.00 for both classification systems. WHR had an importance level of 0.14 and RFD-ratio had an importance level of 0.53. In addition, when BMI was added to the TwoStep analysis for both WHR and RFD-ratio, the average silhouette (the confidence with which the cut-points separate the clusters) either remained the same or decreased. This indicates that the addition of BMI made the cluster association weaker, not stronger as anticipated. Because BMI was such an overwhelmingly strong predictor variable, its presence in the statistical analysis did not increase the strength of the cluster association. As such, the addition of BMI to either the WHR or RFD-ratio classification systems may not be as useful as anticipated in identifying female body types.

5.1.3 Cluster comparisons within body type classification systems

Once the body type clusters had been determined within each classification system, it was then of interest to investigate if and how certain descriptive characteristics varied between the clusters. This was done by comparing descriptive data such as body fat percentage (%), regional and total body fat mass (g), and aerobic physical activity level (min/week) between the three body type clusters that were determined separately using the two measurement systems. The intent of the analysis was to determine if significant differences in selected descriptive characteristics of the female cohort that was studied existed between body type clusters. In theory, such differences would allow health care providers to recognize that females with a certain body type may have clinically significant characteristics that require further testing (i.e. NWO individuals and MONW individuals). Between cluster differences can also help to identify what descriptive data are pertinent for separating subjects within a classification system, and which are not. Descriptive data deemed influential in establishing disease risk can also be included in the assessment during a medical evaluation of women having a particular body type.

5.1.3.1 Cluster comparisons using body fat percentage A One-Way ANOVA indicated that for the WHR classification system, body fat percentage differed significantly between body type clusters. A Tukey *post hoc* test revealed that body fat percentage of subjects in Cluster 1 was significantly higher than that of subjects in Clusters 2 and 3. Body fat percentage did not differ significantly between Clusters 2 and 3. This indicates that Cluster 1 (i.e. the *android* cluster), was associated with a significantly higher overall body fat percentage (mean = 35.5%) than either the *gynoid* (mean = 26.4%) or *hypergynoid* (mean = 23.9%) clusters.

A One-Way ANOVA found significant differences in body fat percentages between clusters as determined by the RFD-ratio method. The Tukey *post hoc* test indicated that body fat percentage of subjects in Clusters 1 and 2 (*android* and *gynoid*, respectively) did not differ significantly. However, both clusters demonstrated significantly greater body fat percentage than Cluster 3 (*hypergynoid*). The *android* cluster had a mean of 29.5% fat, while the *gynoid* cluster had a mean of 26.8% fat, and the *hypergynoid* cluster had a mean of 22.0% fat.

It is important to note that body fat percentage was significantly higher for subjects in the *android* cluster than those in the *hypergynoid* cluster independent of the body type classification system that was employed. Body fat percentage also increased from the *hypergynoid* cluster to the *android* cluster within both the WHR and RFD-ratio systems. As the regional fat distribution changed from the hips to the waist, body fat percentage generally followed in the same pattern, albeit the change was not statistically significant. That is, the mean body fat percentage in Cluster 3 (23.9%) increased to 26.4% in Cluster 2, and reached 35.5% in Cluster 1 for the WHR classification system. Body fat percentage increased from 22.0%, to 26.8%, to 29.5% in Clusters 3, 2, and 1, respectively, when the RFD-ratio classification system was employed.

In the present investigation, the observational trend for increased adiposity across female body type classifications was not statistically significant. Nevertheless, the trend suggests that body fat may tend to be deposited at a faster rate in the abdominal region as it begins to accumulate in healthy, young, Caucasian females. As mentioned in Section 2.1.2, this anatomical variation in fat accumulation is most likely due to differences in the number and sensitivity of β and α receptors found on the adipose cell surface specific to given body regions (34,58). The sample of females employed in the present study appeared to accumulate fat to a comparatively greater extent in the abdominal region. However, some studies have shown that abdominal fat is also lost faster through diet and exercise intervention than occurs for fat found in the femoral region (22,29). From a health care perspective, this anatomically differentiated reduction in fat mass consequent to a weight loss intervention is clinically important as abdominal fat is more strongly correlated with obesity-related diseases than femoral fat (11,20,21,24,25,30,35,37,57,59).

As noted above, the present findings suggested that body fat increased across female body types from *hypergynoid*, to *gynoid*, to *android*, regardless of whether the WHR or RFD-ratio classification system was employed. However, in the present sample, body fat percentage was only moderately correlated to WHR or RFD-ratio (r = 0.491 and 0.553, respectively). Such a moderate correlation was also noted previously between visceral fat and WHR (9). The trend for body fat accumulation to increase across body types from *hypergynoid* to *android* is similar to that found with age, onset of menopause, and parity (10,32,36,38) (i.e. the regional fat distribution shifts from gynoid to android with an increase in these descriptive factors).

5.1.3.2 Cluster comparisons using regional and total body fat mass Comparison of body fat percentage between clusters within each of the two separate body type classification systems demonstrated that absolute measures of adiposity changed systematically from cluster to cluster. However, between cluster differences in regional and total body fat mass may give a different perspective on the distinction between the three body types that were identified. One-Way ANOVAs were performed to determine if either regional or total fat mass differed between body type clusters determined separately using the WHR or RFD-ratio classification systems. The results showed that estimated values of abdominal fat mass, hip fat mass, and total fat mass were all significantly different between the clusters regardless of the classification system used.

In the present investigation, fat mass was estimated according to the equations developed by Ritchie and Davidson (48). Using the WHR classification system fat mass was distributed across body types as follows: the mean regional fat mass in the *android* cluster was 5526.02g for the abdominal area and 6601.79g for the hip area. The total fat mass was 12127.80g. The *gynoid* cluster had regional fat mass means of 3630.60g for the abdominal area, 4930.28g for the hip area, and a total fat mass of 8560.57g. The *hypergynoid* cluster had a regional fat mass mean of 3053.85g for the abdominal area, 4564.96g for the hip area and a total fat mass of 7618.80g. The mean fat mass values for each anatomical area within the *hypergynoid* and *gynoid* body types were not significantly different from each other. However, all three estimated fat mass values were significantly greater for the *android* body type than the other two body type clusters.

For the RFD-ratio classification system, the *android* cluster was found to have a mean abdominal fat mass of 4527.67g, hip fat mass of 5529.32g, and total fat mass of 10056.98g. The *gynoid* cluster had abdominal, hip, and total fat mass means of 3627.71g, 5064.48g, and 8692.19g, respectively. The *hypergynoid* cluster had an abdominal fat mass mean of 2609.41g, a hip fat mass mean of 4158.71g, and a total fat mass mean of 6768.12g. Fat mass values in each anatomical area for the *android* and *gynoid* clusters were not significantly different. The *hypergynoid* cluster had significantly less regional and total fat mass than was estimated for the other two body type clusters.

In the present investigation, significant differences were found in estimated fat mass between body type clusters within both classification systems. These results indicate that young, healthy females tend to accumulate fat mass in the abdominal region to a greater extent than in the hip region. Specific to the subject sample studied, it appeared that females with a *hypergynoid* body type tended to have less fat mass then observed for the other two clusters, regardless of the anatomical area of measurement. A significant statistical difference in regional and total body fat mass was observed between the clusters regardless of the body type classification system that was employed. Initially, the TwoStep cluster analysis separated subjects into three distinct clusters based solely on WHR or RFD-ratio. It was recognized that if there is no impact on body type due to fat mass, each anatomical area of interest (abdomen, hips, or total) would have a similar mean fat mass between body types. However, significant differences in estimated fat mass values for a given anatomical area were observed between clusters (Table 15). This indicates that the amount of fat mass per anatomical area may influence body fat distribution. These findings generalize to both the WHR and RFD-ratio systems to classify female body type.

Previous investigations have examined body fat distribution according to body type classification using measured or calculated fat mass as the comparative variable (27,28,29,41,42,43,49). However, some studies only used total body fat mass (28,42) as it was easier to determine. Other studies used more definitive methods to anatomically regionalize fat mass measures to visceral, subcutaneous, and/or peripheral compartments (27,29,41,43,49). In those studies where gynoid and android obesity body types were compared, differences in total body fat mass between the body type groups were examined statistically (28,42). However, when regional body fat mass was determined through CT tomography or DXA, the measured value was typically used as a descriptive characteristic, rather than a variable that was compared between body type groups (27,29,41,43,49).

Based on published literature, it appears that previous investigations have not compared regional body fat mass as a single variable across body types. Typically, when subjects are divided into body type groups, weight or BMI is also used to further delineate the groupings. For example, subjects are categorized by body type (lower body obese and upper body obese) then by BMI (lower body obese and upper body obese versus non-obese subjects). The current investigation initially clustered subjects solely on calculated fat distribution, regardless of weight or BMI. Follow-on analyses showed that the addition of BMI to the calculation did not improve the cluster quality. In this regard, the current study is unique in its comparison of regional fat mass between body type clusters independent of other descriptive characteristics, particularly in a young, healthy, Caucasian female subset.

5.1.3.3 Cluster comparisons using physical activity level Regardless of whether WHR or RFD-ratio was used as the system to classify female body types, aerobic physical activity level (min/week) did not differ significantly between the three body type clusters that were identified. Across the three clusters within both body type classification systems, aerobic physical activity participation ranged from 151.03 min/week to 259.40 min/week. The standard deviations almost equivalent to the cluster means. This lack of significant difference between body type clusters indicates that aerobic physical activity level does not affect cluster assignment. Though not statistically significant, it is interesting to note that within both classification systems, the *gynoid* group (Cluster 2) had the lowest aerobic physical activity level of the three clusters. The lack of statistical significance between the clusters indicates that the amount of weekly aerobic physical activity may not influence the body fat distribution in the young Caucasian females that were studied.

The effect of aerobic physical activity level on body fat distribution in females has not been widely studied. The majority of studies investigating change in body fat distribution in relation to weight gain or loss have employed dietary caloric restriction as the intervention strategy (4,9,22,29,50). However, Tremblay et al. found that those individuals who performed vigorous aerobic physical activity on a regular basis had a lower WHR than those who did not (52). The present investigation did not take into account the aerobic physical activity intensity, only the amount of participation time. Although the findings were non-significant, the current study suggests that for both body type classification systems, subjects in the *hypergynoid* cluster exhibited comparatively greater minutes per week of aerobic physical activity. This observation is consistent with previous literature.

Despite the observation that weekly aerobic physical activity levels were not significantly different between body type clusters, the results from the current study can be helpful for weight management planning and health-fitness programming. The present findings indicated that the amount of aerobic physical activity performed throughout the week did not explain differences in body fat distribution according to body type clusters. Future research should focus on weight loss programs centered around other aerobic physical activity dimensions such as exercise intensity or mode. Such knowledge can help health-care and fitness professionals develop more robust and individualized intervention plans, rather than simply focusing on one aspect of an exercise participation.

5.2 SECONDARY FINDINGS: INTERCHANGEABILITY OF BODY TYPE CLASSIFICATION SYSTEMS

A secondary objective of this investigation was to determine if the two body type classification systems identified clusters that were similar enough to be used interchangeably. One of the main goals for development of new body type classification systems was to make the process for determining female body type easy enough that it would be of use to the general population. It has already been established that the WHR as compared to the RFD-ratio system is the easier of the two to implement. This is because the RFD-ratio classification system uses equations that are complex and as such require time to calculate. Ultimately, this methodological limitation makes the RFD-ratio system impractical for large scale application.

However, the RFD-ratio procedure should not be discounted as a viable body type classification system. Further study of the RFD-ratio system should be undertaken to determine if in fact it can predict obesity-related disease-risk to the level of other classification systems. A study performed by Ito et al. (27) indicated that the ratio of trunk fat mass divided by the leg fat mass predicted cardiovascular risk factors similarly or better than the WHR in a sample of Japanese women. Since it is plausible that the RFD-ratio is at least as good, if not better, than the WHR in predicting obesity-related disease risk factors in a young Caucasian female population, it is important to continue to investigate this method of body type classification. The major limitation of the RFD-ratio classification method is the complexity and time involved in calculating the fat mass of each anatomical area, then finding the ratio of these values. It would be advantageous to determine if the RFD-ratio and WHR classification systems are similar enough to be used interchangeably. If such similarity is demonstrated, then the WHR body type classification system could be used. This application combines the ease-of-use of the WHR system with the comparative accuracy of the RFD-ratio system.

The first step in exploring interchangeability was to compare the ratio for a given cluster between the two body type classification systems. As an example, the *android* cluster determined by the WHR system was compared to the *android* cluster determined by the RFD-ratio system using a One-Way ANOVA. This test verified whether the mean ratio of the subjects with a given body type cluster in one classification system differed significantly from the mean ratio in the corresponding cluster as determined by the other classification system. If the mean ratio of subjects did not differ, then a correlation and regression analysis was to be performed. Such a correlation analysis was intended to determine whether using the methodology for one body type classification system would accurately place a subject into the corresponding cluster formed by the other body type system.

However, the One-Way ANOVA demonstrated that the mean value for a given cluster in the WHR system and the mean value for a comparable RFD-ratio cluster differed significantly from each other. This indicated that the two body type classification systems are not interchangeable. This result was not unexpected, as measurement systems such as DXA (which the RFD-ratio equations are based on), MRI, or CT scans determine subcutaneous and visceral fat differently and more precisely than anthropometric measurement systems such as WHR, WC, or BMI. This discrepancy in classification assignment existed even though both types of systems used presently predict obesity-related diseases with equal power (8). In the present investigation the ratios of subjects placed in any two corresponding body type clusters were significantly different. Never-the-less, a Pearson correlation analysis was calculated to determine the relation between the WHR and RFD-ratio clusters. The resulting correlation coefficient was statistically significant at r = 0.652. However, this coefficient demonstrated only a moderately-strong correlation between the two classification systems. This correlation coefficient only explained 42% of the variance between the cluster ratios formed by the two classification systems. The findings further support the conclusion that the two body type classification systems examined presently are not interchangeable methodologies.

5.3 CONCLUSIONS

Two different anthropometric-based measurement systems were used to develop female body type classification continua. Among a sample of healthy, young, female Caucasians, three main body types appeared to form naturally, regardless of whether the classification system was based on WHR or RDR-ratio methodology. These clusters align well with previously established *hypergynoid*, *gynoid,* and *android* female body type groupings (4,32,53). Due to difficulty recruiting subjects with a high BMI and WHR, it is unknown if a fourth, *hyperandroid*, group would emerge as a body type cluster for this cohort. However, based on the few subjects that had a WHR greater than 0.8, it is very probable that as hypothesized, a *hyperandroid* cluster exists for female body types. With regard to the current female sample, of those subjects considered within the “normal weight” BMI category (18.5-24.9 $kg \cdot m^{-2}$), none had a WHR at or higher than 0.8, and only two subjects had a WHR higher than the naturally formed cluster cut point of 0.78.

5.3.1 Body type classification systems developed on a baseline sample

One drawback of this study is that the subject sample had narrow demographic characteristics. Only healthy Caucasian females, aged 18-29 years, who had never been pregnant or smoked, were allowed to participate in the study. This comparatively narrow range of *a priori* selected descriptive characteristics may be one of the reasons for the difficulty experienced in recruiting subjects with a high WHR. However, it is important to initially establish a body type classification system using a "baseline" population sample to help better determine if follow-on investigation should account for the effect of such factors as age, health, smoking, etc. on female body type.

Had the body type classification systems included females, regardless of age, health, ethnicity, or parity status, the cluster cut-points, especially for the middle cluster, would likely be much farther apart. This is because these factors are correlated with an increase in abdominal fat (9,10,23,36,38,41). For example, if females who smoked had been included in the sample, the *gynoid/android* cut-point may have fallen at 0.82 in the WHR classification system instead of 0.78. Thus, if a healthy-appearing female presents with a WHR of 0.80, they would fall in the *gynoid* cluster, and the WHR would not provide helpful clinical information to the health care professional. However, when a body type classification system is built on healthy females with no confounding factors (i.e. ethnicity, smoking habits, parity status, etc.), a female with a WHR of 0.8 may alert the health care provider to raise the level of evaluation as the *gynoid/android* cut point is 0.78. As both classification systems were built on a baseline population sample, any female presenting with a WHR or RFD-ratio above the *gynoid/android* cut-point may warrant further clinical attention and testing.

In this same context, multi-factor body type classification systems could be developed wherein the female body types identified presently are used as baseline continua. For the present investigation, the “baseline continua” were developed for a cohort of healthy, young, females who do not smoke and have not had children. In future investigations, demographic factors that may relate to body type classification for females could then be incorporated into the cluster analysis. Based on previous reports, such factors as ethnicity (23,41), tobacco smoking (9), and/or parity status (10,36,38) may affect female body type. Such descriptive research may refine the derived body type clusters. Their application in a clinical setting would be simple, providing comparatively more useful information than separate application of WHR, WC, or BMI measurements. This individualization of body type classification may not seem as necessary with overweight or obese individuals for whom the disease-risk is already known to be high. However, the classification systems could help to identify females, such as those MONW (31), who should undergo more extensive testing and receive appropriate preventative care where they otherwise would not.

5.3.2 Body type classification based on WHR versus RFD-Ratio

As noted in the Introduction, this investigation projected three main application goals. The first goal was to create a system that classified female body types based on natural clustering. This goal rejected the traditional classification methodology based on *a priori* defined body type groupings. The second goal was to develop a generalizable body type classification system that included normal weight, overweight, and obese subjects equally, not just the latter two types of individuals who had been studied previously. The final and most important goal was to develop a classification system that was simple enough to use in an everyday clinical and/or health-fitness setting. It was reasoned that if the methodology was complicated or time-consuming, it would be difficult to implement in day-to-day assessments.

With these application goals in mind, two body type classification systems were designed – one based on body circumference measurements (WHR), and one based on fat mass determined using prediction equations derived from DXA measurements (RFD-ratio). The second system also included several anthropometric measurements. However, these anthropometric measurements were used as part of the fat mass equations rather than employed independently to provide a ratio from which body type was directly determined. Both classification systems produced three naturally occurring female body type clusters – *hypergynoid*, *gynoid*, and *android*. However, an ANOVA and Pearson Correlation indicated that body type assignments to these clusters were not interchangeable across classification systems.

If these systems are not interchangeable, then which one is more accurate and practical for broad-based clinical and health-fitness application? As the present study was preliminary in design, it did not examine the subjects' health status, focusing only on determining the separate body type clusters. Based on ease of use, the WHR body type classification system is simpler and faster to use than the RFD-ratio system. However, it would be prudent to investigate which system better detects disease-risk before discarding RFD-ratio as a useful body type classification system.

5.4 RECOMMENDATIONS

The primary purpose of this study was to determine if body type classification systems could be created based on measures of either WHR or RFD-ratio. The research rationale projected three key application goals with the intent of keeping the classification systems easy to use while still maintaining a high level of discrimination between body type clusters. First, the classification systems needed to be based on naturally occurring body type clusters. Second, the subject sample used presently was to be equally distributed between normal weight, overweight, and obese individuals. Third, the method of determining female body types was to be simple enough to be used on a day-to-day basis by health care and physical activity specialists.

The first application goal of the study was met through the use of a TwoStep cluster analysis. The TwoStep cluster analysis allowed the formation of good quality clusters without influence of a predetermined number of clusters or set ranges of the criterion variable. While this analysis works well for most sample sizes, it was not possible to be determine the smallest sample that could still provide a strong effect size. Thus, it is recommended that future studies use a comparatively larger population sample size than employed presently to increase the strength of the effect size.

The second goal of the investigation was to include normal-weight individuals in at least the same numbers as overweight or obese subjects (as determined by BMI). Of 73 subjects assessed, 71% were considered normal-weight, 18% were overweight and 4% were obese. While the study reached its goal of including at least 50% normal-weight subjects, the sample size for the three weight groups was still not equivalent. In order to determine the most accurate body type continuum regardless of classification system used, *a priori* determined BMI groups should contain equal numbers of subjects.

Although the present findings determined that BMI should not be used in conjunction with the ratios to form the body type classification clusters, the inclusion of higher BMI subjects increases the likelihood of higher WHR and RFD-ratios. The lack of overweight and obese individuals in the subject pool employed presently most likely is the reason a fourth cluster (*hyperandroid*) did not emerge from the analysis. Only two subjects exceeded the traditional 0.80 WHR cut-point used to determine those individuals at a high disease-risk owing to excess body weight. As such, there were simply not enough subjects to determine if the *hyperandroid* cluster appeared in the female body type continuum. It is known that individuals with a WHR above the 0.80 cut-point do exist, but they are also more difficult to recruit for research studies. It is strongly recommended that future investigations use a population sample that consists of a higher percentage of females that fall into the overweight and/or obese categories.

The third goal of the study was to develop female body type classification systems that could be easily used by the general population. The WHR body type classification system is very easy to use and simple to calculate. It is proposed that a majority of the general population is able to use a measuring tape to determine the circumference of the waist and the widest part of the hips. Thus, the two anthropometric measures necessary to compute the WHR can be performed independently by the individual themselves. The RFD-ratio measurements are also easy to understand and perform. However, the insertion of those measurements along with the BMI into a prediction equation is not easy to accomplish for a significant portion of the general population. The equations are too complex to memorize and their calculation may be too time consuming for clinical use.

As mentioned above, the methodology of this study only permitted determining the natural formation of clusters within a body type classification system. Given the type of data that were collected, it was not possible to determine if either the WHR or RFD-ratio body type classification system was the better predictor of obesity-related disease risk in young women. It is recommended that the next research step be to gather health-related data (such as lipid levels, blood pressure, insulin and glucose sensitivity, etc.) to compare across the body type clusters determined by both the WHR and RFD-ratio systems. Once these data are collected and analyzed, it would then be possible to compare the two classification systems and determine if one or both consistently predict if an individual had any disease-risk factors. It is hypothesized that either a WHR or RFD-ratio above the *gynoid/android* cut-point would indicate an increase in the risk of developing obesity-related diseases, regardless of BMI. If this holds true, early testing (i.e. pro-active) could be performed on these individuals (especially normal-weight individuals who would otherwise not be candidates for further evaluation) and preventative care could be given.

APPENDIX A

PHYSICAL ACTIVITY QUESTIONNAIRE

ID # ______________

University of Pittsburgh
Center for Exercise and Health-Fitness Research

Physical Activity Questionnaire

YES/NO

1. Do you participate in weekly aerobic exercise? ________

    A. If yes, how many days per week? __________

    B. How many minutes per exercise session? __________

        i. Total minutes per week? __________

    C. What types of exercises? ____________________________

2. Do you participate in any college or professional athletics (i.e. NCAA, club, etc.)? ________

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