A new index to replace Body Mass Index (BMI) as an indicator of fat mass.

Neil Pheasant

A thesis submitted to Auckland University of Technology in partial fulfilment of the requirements for the degree of Master of Sport Exercise and Health

2024

Faculty of Health and Environmental Sciences

Table of Contents

Tables

Figures

Attestation of Authorship

"I hereby declare that this submission is my own work and that, to the best of. my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor used artificial intelligence tools or generative artificial intelligence tools (unless it is clearly stated, and referenced, along with the purpose of use), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning."

Neil Pheasant

August 2024

Acknowledgements

No one truly prepares you for the transformative journey that a thesis demands. From the intricacies of completing ethics applications and meeting with faculty specialists to the highs of great productivity and the lows of unproductive droughts, it's an emotional rollercoaster. Without the steadfast support of my supervisors, this journey would have been significantly more challenging, if not impossible.

To Hannah, my primary supervisor—my deepest thanks. I couldn't have asked for a better guide through this journey. Your unwavering support, always available without applying pressure, has been nothing short of invaluable. You were there to discuss problems, share ideas, challenge my thinking, and encourage me to see both writing and life from new perspectives. Your calm and reassuring presence kept me grounded and on track, even when life didn't go quite as planned. Despite your transition to a new role at a different university, you continued to supervise me with weekly calls, a commitment for which I am eternally grateful.

To Andy, my secondary supervisor—thank you for being a constant support in the background. Your willingness to assist whenever needed and the valuable insights offered has been incredibly appreciated. Stepping in as my primary supervisor to help bring this thesis to completion was a crucial contribution, and I am deeply thankful for your guidance.

To Alan, my external supervisor—my friend, and my mentor, your encouragement set me on this thesis journey, and your belief in my abilities gave me the confidence to continue. You set a fantastic example for me to live up to in all aspects of life. Thank you for your encouragement, consistent support, and for always being there to offer your time and guidance throughout this process.

Lastly thanks to my partner Julia for her support during the ups and downs and her encouragement throughout the process.

To all of you, I offer my heartfelt thanks for your dedication, encouragement, and belief in me. This thesis would not have been possible without your unique and invaluable contributions.

Ethical approval for this research was granted by the Auckland University of Technology Ethics Committee (AUTEC). Approval was originally granted on the 27th of January 2023 under the reference 22/384.

Abstract

Objective: Body Mass Index (BMI) has long served as the standard metric for classifying obesity, estimating fat mass, and assessing related health risks. However, BMI's limitations in accurately reflecting fat distribution and predicting individual health outcomes have become increasingly apparent, especially regarding gender differences, cultural variations, and athletic body types. This research aims to develop a novel index that addresses some of BMI's limitations by incorporating body shape alongside overall body size. The main objective of this thesis was to investigate the contribution of anthropometric measures to estimating fat mass. A secondary objective was to evaluate the effectiveness of a novel index for estimating fat mass across different subgroups defined by sex and ethnicity.

Methodology: A cross-sectional observational design was used, sampling adults from New Zealand across the four primary ethnic categories: Māori, European, Asian, and Pacific Islander. A total of 99 participants (49 males and 50 females) aged between 18 and 83 years were included. The measurements collected from participants included weight, height, waist/hip circumference, and eight skinfold sites. Body fat percentage (%BF) was estimated using validated bio-impedance equipment (Tanita BC420MA).

Pearson's correlation coefficients (r) were calculated to quantify the relationships between %BF and BMI, and %BF and the new Bodyfat Distribution Index (BDI), in order to compare their predictive accuracy of %BF. Linear regression analysis was performed to assess the relationship between %BF and both BMI and BDI, with comparisons across gender and ethnicity to assess their predictive ability to distinguish between the groups.

Results: BDI accounted for 60% of the variability in %BF, compared to BMI, which accounted for 45%. Utilizing BDI Females still have greater scores than males for the same %BF, but the sex differences are markedly less than for BMI.

Conclusion: The BDI, a simple novel index, provided a more comprehensive estimate of %BF than BMI, successfully addressing some of BMI's key limitations, offering improved differentiation between genders, and partially accounting for ethnic variations.

Future Direction: This study underscores the potential benefits of a simple new index to improve health assessments, interventions, and outcomes, particularly in New Zealand's urban and remote rural populations, where access to advanced medical facilities may be limited. By leveraging mobile

technology, such as smartwatches and smartphones, a simple novel index focusing on fat mass distribution could offer a more accurate measure of body composition. If digitized into an app, this novel index could improve accessibility and enable more effective, personalized health strategies and outcomes. This approach to estimating %BF may help reduce the stigma associated with BMI classifications, fostering a more nuanced understanding of health.

Chapter 1 Introduction and Rationale

The accurate measurement of fat mass has been a longstanding concern in epidemiology, public health, and clinical medicine due to the profound implications increased fat mass has on health. Excess fat mass is strongly linked to a decline in quality of life, an increased risk of cardiovascular and metabolic diseases, and elevated morbidity rates (Frank et al., 2019; Pi-Sunyer, 2002; Walls et al., 2012). For over five decades, the evaluation of health through body size has been a focal point for practitioners, researchers, and the public (Fletcher, 2014; Gutin, 2018). Obesity, can be defined as abnormal or excessive fat accumulation that poses a risk to health (Bjorntorp, 2002; Bray, 2014; Bray & Popkin, 1998), is closely tied to increased intra-abdominal fat (Smith et al., 2001). Despite the widespread use of Body Mass Index (BMI) in epidemiological studies to classify overweight and obesity (Chooi et al., 2019; Frankenfield et al., 2001; Prentice & Jebb, 2001), BMI's low sensitivity and inability to differentiate between fat mass and lean mass limit its usefulness. Variations in body fat percentage across individuals, influenced by factors such as age, sex, and ethnicity, further complicate the use of BMI as a reliable measure (Chooi et al., 2019). As the global prevalence of obesity continues to rise, so too does the need for more precise methods of fat mass estimation to better assess health risks across diverse populations (Peltz et al., 2010; Stein & Colditz, 2004). In New Zealand and around the world, obesity has become one of the most pressing public health issues (Bassett & Perl, 2004).

Among the various estimates of fat mass, BMI has traditionally been the preferred estimate of adiposity (Gutin, 2018; Jackson et al., 2002) and is commonly used to distinguish healthy from unhealthy in all forms of communication from the media to scientific literature (Saguy & Almeling, 2008). As our understanding of obesity and its health consequences deepens, it is increasingly evident that BMI falls short of capturing the nuances of fat mass distribution within the human body (Burkhauser & Cawley, 2008). The limitations of BMI have become more apparent with changing environments, diets, technology, evolving scientific knowledge, and the need for a broad understanding of body composition. BMI incorrectly classified 62% of adolescent athletes as obese when compared to fat mass estimation using skinfold measurement (Etchison et al., 2011). Since the introduction of BMI, numerous advanced techniques to estimate fat mass have developed. The most common are underwater weighing, dual-energy x-ray absorptiometry (DXA), Computed Tomography (CT), Bio Impedance Analysis (BIA), and magnetic resonance imaging (MRI). Although advanced technology now exists for more accurate fat mass estimation, a simple index, which does not require expensive and specialised technology, is still advantageous. BMI fits the need for simplicity, but as a tool for estimating body composition at the individual level, BMI performs poorly compared with modern body imaging methods and is unable to differentiate important body mass components (Swainson et al., 2017).

Previous studies support the necessity for an alternative to BMI to estimate body fat percentage in the clinical setting that has a better relationship to health and mortality (Nuttall, 2015; Peltz et al., 2010). Notably, findings from medical literature suggest that the amount of fat is important, but the location and distribution of fat matter as well (Gallagher et al., 1996; McCarthy, 2006; Smalley et al., 1990; Yusuf et al., 2005). Abdominal visceral fat is associated with an increased risk of morbidity (Bray & Popkin, 1998). Abdominal subcutaneous fat is highly correlated with waist circumference, which is indicative of body shape, and this reference to body shape is what previous indices failed to consider (Browning et al., 2010). BMI has remained popular because it is simple (Burkhauser & Cawley, 2008). However, given the shortcomings of BMI and the importance of fat mass in clinical diagnosis, the inclusion of a shape measurement considering both overall body size and shape will allow better estimation of fat mass and the associated health risks, and, therefore, to improved personalised health recommendations and interventions (Browning et al., 2010). Therefore, there is the potential to integrate easy-to-measure anthropometric variables (not accounted for by BMI) into a novel index without making it impractical to obtain.

This study will explore literature to critically evaluate the prevalence of obesity as classified by BMI and other popular existing indices and discuss the relationship between BMI and health. The research design, data collection methods, and analytical procedures will be detailed, followed by an evaluation of the findings. A novel body composition index will be proposed that will aim to combine accuracy, simplicity, and practicality, and provides more accurate and straightforward estimation of fat mass that could enhance accessibility in New Zealand's rural areas and provide more precise estimation of an individual's risk of weight-related diseases.

Thesis Aim and Research Questions

Fat mass (FM) is a critical component of total body mass and has been increasingly linked to negative health outcomes (Flegal et al., 2013). While BMI is the most commonly used measure to estimate fat mass, it fails to differentiate between fat and lean mass, and overlooks important variations related to sex and ethnicity. This research will incorporate a range of anthropometric measures that account for body mass, size, and shape, with the aim of providing a more accurate reflection of body morphology than BMI alone. The idea to incorporate shape-related metrics into a new index, particularly those associated with the distribution of body fat like Waist to Height Ratio was a personal reflection which under analysis could address selected BMI's shortcomings. Ensuring that the measures are easy to use will encourage broader adoption, especially in New Zealand, were geographic and ethnic diversity present unique challenges for health assessment.

Therefore, the main aim of this thesis is to investigate the contribution of anthropometric measures to the estimation of fat mass. A secondary objective is to evaluate the use of a novel index for estimating fat mass across different subgroups of sex and ethnicity. To achieve this, the four research questions (RQ) to be addressed are:

RQ1) Does BMI predict fat mass as a percentage of body mass for a sample of the New Zealand population?

RQ2) Which anthropometric, composition and personal variables best predict fat mass as a percentage of body mass?

RQ3) Does a novel index incorporating shape better predict fat mass than BMI?

RQ4) Can a novel index better distinguish fat mass between participants of different sex and ethnicity than BMI?

Significance of the thesis

New Zealand's low population density, particularly outside its major cities, presents significant challenges in accessing effective methods of health assessment. Many individuals reside in small towns, rural areas, and on outlying islands, where access to advanced health measurement technologies can be limited. Given these circumstances, a simple and accessible measure of body fat, with minimal reliance on sophisticated technology, would be well-suited to the country's population. A novel body composition index, delivered through a smartphone application, has the potential to enhance public health by empowering individuals to assess their own body composition. This approach could improve understanding of personal health and body mass, providing a more tailored assessment than BMI.

The research presented in this thesis aims to lay the groundwork for a novel index, which could eventually be developed into an accessible application. Evidence suggests that the availability of mobile health applications supports and encourages individuals in evaluating their own body composition and understanding its impact on overall health (Jutel, 2009; Rich & Evans, 2005). Developing a novel index to estimate fat mass more accurately is critical for better assessing health risks and providing more personalized health recommendations. Additionally, incorporating factors like gender and ethnicity in health evaluations could help reduce discrimination associated with BMI-based classification, offering a more inclusive approach to health management.

Chapter 2 Literature Review

Measures of Fat

The literature review explores the historical development and use of BMI as an estimate of body fat covering its strengths and limitations and will review indexes that have been proposed as alternatives to BMI. Additionally, the review will cover various methods for estimating body fat, including both manual techniques and advanced imaging technologies. The relationship between these estimates and health outcomes will be examined.

History of BMI

Initially a population-based assessment, BMI was never intended as a readily available individual health assessment (Burkhauser & Cawley, 2008; Gutin, 2018). The Quetelet index, the precursor to BMI, was introduced by Adolphe Quetelet to indicate adolescents' expected growth rate using the equation weight/height^2 (Quetelet, 1842). Considered a founder of social sciences and the patriarch of statisticians, Quetelet was a mathematician and statistician whose goal was to determine the characteristics of the 'average man' and use the Gaussian distribution to describe the variation of characteristics from the average (Eknoyan, 2008; Nuttall, 2015). Quetelet's index was popularised in population-based studies by Keys referring to it for the first time as Body Mass Index, the ratio of body mass to the square of stature, that has become a universal indicator of clinical obesity in an individual despite its original purpose as a population based index (Keys et al., 1972).

The Metropolitan Life Insurance Company was the first to classify obesity and its associated risks. The company research showed that weight/height was an independent determinant of life expectancy in data collected from insured men by 26 different life insurance companies between 1935 and 1953 (Gutin, 2018; Nuttall, 2015). The validity of the Metropolitan life insurance data and the published tables of desirable weight were however criticized by Keys. In his seminal paper "Indices of relative weight and obesity", published in 1972, Keys used better documented data including height, weight, and skinfolds from 7426 men from the USA, South Africa, Japan, Finland, and Italy and analysed the correlation of four indices of relative weight with height and weight. The four indices were: the ratio of weight to height (W/h), the Quetelet index (W/h^2), the Ponderal index (W/h^3), and weight as a percentage of the average weight for a given height and age. Keys concluded that any relative weight index should be uncorrelated with height because body shape does not remain constant as height increases but should be strongly correlated with weight. On that basis, Keys considered the Quetelet index as the best of the four studied (Keys et al., 1972).

The Metropolitan life insurance tables continued to be used until the 1990's despite the critique from Keys (Must et al., 1991) and were replaced only when the World Health Organisation (WHO) assembled an expert consultation group in 1993 charged with developing uniform categories of BMI. BMI's popularity surged following the results of the report "Use and Interpretation of Anthropometry", which published classifications of body weight for height, based on BMI *Table 1* (World Health Organization, 1995). The classification was expanded by the WHO International Obesity Task Force in 1997 and pre-obesity was introduced to replace the overweight category and obesity was classified into three groups (World Health Organization, 2000). Mean BMI in Western population-based studies is 24-27 (Nuttall, 2015), which means that more than 50% of the population is classed as pre-obese and obese by the WHO classification. The terminology in *Table 2* comes into question because BMI is not a direct indicator of fat mass and so those in the overweight category who are now classed as pre-obese may be classified incorrectly (Nuttall, 2015).

Table 1:Categories of BMI developed by WHO.

Categories of BMI	
Underweight	15 – 19.9
Normal	20 – 24.9
Overweight	25 –29.9
Obese	30 – 35 or greater

Table 2:Categories of BMI and degrees of obesity developed by the WHO International Obesity Task Force

Categories of BMI	
Underweight	15 – 19.9
Normal	20 – 24.9
Pre-obesity	25 –29.9
Class I Obesity	30 – 34.9
Class II Obesity	35 – 39.9
Class III Obesity	≥40

Body Mass Index, linked to obesity by the WHO classification index (World Health Organization, 2000), has gained more attention in recent years with the emergence of the obesity epidemic (James et al., 2001). High body mass, as measured by BMI, is often seen as a direct cause of morbidity and mortality, rather than a contributing factor. As a result, individuals classified as overweight or obese by BMI frequently face discrimination due to their size and shape. This stigma is further reinforced by mass media, which often portrays “fat bodies” as inherently unhealthy or diseased (Saguy & Almeling, 2008). There is a section of the population, for example sportsmen and women, that are classed as fat by mass and BMI but who are in fact fit by health standards and not at risk of early mortality (Nuttall, 2015; Sims, 2001). As an index of obesity, BMI does not differentiate between lean body mass or fat body mass, conversely a person can have a low BMI but a high fat mass (Flegal et al., 2009; Wellens et al., 1996).

Body Mass Index is still widely used to define specific categories of body composition in many populations since it is a simple way to track obesity on a population level (Prentice & Jebb, 2001). BMI is used extensively in population and medical research with over 8000 articles referencing “body mass index” in 2017 alone (Web of Science) and it has long been the index of choice for epidemiological purposes because it is easy to calculate (Gutin, 2018). The ubiquity and simplicity of BMI support its consistent use as a risk factor in the incidence of many health issues (Gutin, 2018), a factor in determining public health policy (Nuttall, 2015), an indicator for access to specific jobs (Roehling et al., 2007) and a variable to project premiums for life insurance (Dhurandhar, 2016). The limitations inherent in BMI in distinguishing between lean body mass and fat mass, as well as its inability to account for age, gender, ethnicity, and variations in fat distribution have spurred considerable debate within the scientific communities despite its popularity. Over the years since Keys’ 1972 summation, the limitations of BMI have been cited many times (Blackburn & Jacobs Jr, 2014). The accuracy of BMI has been questioned (Flegal et al., 2009), new categories of BMI have been proposed and alternative indexes have been introduced (Radetti et al., 2021). However, nothing as simple as Quetelet’s BMI has materialised in more than 180 years (Gutin, 2018).

Alternatives to BMI

Exploring new methods to obtain accurate body composition data is necessary to overcome the limitations of indices such as BMI (Shiely & Millar, 2021). For an anthropometric index to be used in a public health context, it must remain simple to measure and calculate (Nuttall, 2015). There have been many proposed alternative indices and, in recent years, many websites with BMI-related calculators have appeared, which simplified the process of obtaining BMI, but also added to the confusion of the relationship between body mass and health (Gutin, 2018). The indices reviewed here, the Ponderal Index, Waist to height ratio, BMI self-selection, and New BMI height exponent of 2.5 were chosen because they are the most frequently reported when searching epidemiological literature.

The Ponderal Index

In the early 1800's the first to suggest the index mass divided by height cubed was Buffon who believed that a person's mass does change relative to their height (Burton, 2007). The height cubed index first named the "indice ponderule" or later Ponderal Index (PI), proposed a ratio that calculated, what at the time was best described as body bulk using height and weight, dividing mass in kg with the third power of height in metres (Florey, 1970). The Ponderal Index reflected a proportional weight change with height and was introduced to measure human leanness. The Ponderal Index is notably a better representation of body mass than BMI when considering people both taller and shorter than average height (Ditmier, 2006).

Keys analysed PI and other indices in his seminal paper originally published in 1972 (Keys et al., 1972) using insurance industry tables. Keys questioned how a single linear dimension of height could be used to accurately reflect body mass distribution because mass is related to volume and, therefore, requires three linear dimensions (Blackburn & Jacobs Jr, 2014).

The Ponderal Index was less popular than the Quetelet index in the 1800s because it was more difficult to calculate manually and, without calculators, errors were commonplace (de Saint-Genoisstraat). The PI is often confused with the Corpulence Index (CI) or Rohrer's Index, which was introduced by Fritz Rohrer in 1921. The difference is that the Rohrer index is a factor of 10 smaller because it uses mass in grammes and height in centimetres, and is like the Infant Ponderal Index (IPI) (Peterson et al., 2017). The IPI is still used frequently in paediatrics to assess whether a new-born baby is malnourished, healthy, or overweight and in conditions such as intrauterine growth restriction. Quetelet recognised that a persons weight increases more slowly as they grow and made this point in 1842:

"If man increased equally in all dimensions, his weight at different ages would be as the cube of his height. Now, this is not what we really observe. The increase of weight is slower, except during the first year after birth; then the proportion we have just pointed out is pretty regularly observed"(Quetelet, 1842).

So, the continued use of PI in new-borns is accepted as weight does increase approximately as height cubed. Although PI reflects average body density, it has no way of assessing body shape and is limited in its application because, like BMI, it does not distinguish between fat and lean muscle mass in estimation of body composition.

Waist to height Ratio (WTHR)

The ratio of waist circumference to height (WTHR) first gained popularity at the end of the last century and, like BMI, it was considered simple and applicable to a wide variety of populations (Browning et al., 2010). Analysis of WTHR used data from the 1992 health survey for England with a sample of 1411 men and 1481 women aged 30-74 (Ashwell & Lejeune, 1996). WTHR is an indicator of body shape. However, WTHR is commonly used as an indicator of body composition when screening for obesity and risk of cardiovascular disease and diabetes because waist circumference is associated with measures of abdominal fat from advanced imaging techniques that show internal visceral fat deposits (Browning et al., 2010). Visceral fat poses a greater risk to health and cardio-vascular disease than fat stored elsewhere in the body (Hsieh & Yoshinaga, 1995; Yoo, 2016). WTHR is calculated by dividing the waist by height in the same units of measure and is used to categorise people into six groups (Ashwell M. et al,. 2009) *Table 3.*

Table 3:Categories of Waist to Height Ratio

Rating	Men	Women
Extremely Slim	≤0.34	≤0.34
Underweight	0.35-0.43	0.35-0.41
Healthy	0.44-0.52	0.42-0.48
Overweight	0.53-0.57	0.49-0.53
Very Overweight	0.58-0.62	0.54-0.57
Morbidly Obese	≥0.63	≥0.58

WTHR is a better indicator of total body fat than BMI and it allows for self-measurement in any setting because it requires only a tape measure (Browning et al., 2010). The 2010 systematic review of published studies by Browning concluded, "WTHR may be advantageous because it avoids the need for age-, sex- and ethnic-specific boundary values" (Browning et al., 2010). However, there are researchers who believe that different cut-off points and anthropometric measurements are required when assessing ethnic and racial variation among the population from different regions (Park et al., 2009). Tailoring health assessments to better reflect the diversity of human populations is important and aligns with growing evidence that standard BMI measurements may not actually capture body fatness across different ethnic groups because of variations in body composition and fat distribution (Rush et al., 2009). WTHR is also limited because it does not distinguish between fat and lean muscle mass when estimating body composition and may not estimate the health risks for tall and short individuals with similar waist circumference accurately (Browning et al., 2010).

BMI Self Selection (BSS)

BMI Self Selection is calculated by the participant selecting one of the four categories in which they estimate themselves to be, underweight, normal, overweight, or obese. This method was introduced to explore accuracy in assessing BMI in extensive epidemiological studies and analysis of 1,354 men and women aged 51–77 years resulted in 59% underestimating their BMI (Shiely & Millar, 2021). BSS, alongside BMI, often relies upon self-reported weight and height. However, self-reported weight is often significantly undervalued (Brug et al., 2006) compared with height which is mostly overestimated (Robinson & Oldham, 2016). Inaccurate determination of BMI can lead to underestimating obesity and various health conditions (Shiely & Millar, 2021) and overestimation of obesity in the population who are at a healthy weight (Brug et al., 2006) including athletes or physically muscular individuals. A 5% reduction in mass and a 5% increase in height will generate about a 10% reduction on BMI. So, a true BMI of 30 would go down to 27. Consequently, use of BSS to estimate BMI can lead to underestimating obesity.

BSS is a simple method but requires participants to understand existing BMI categories well. BSS may be influenced by gender, the level of a participant education (Shiely & Millar, 2021), and environmental factors such as using the people around us as our reference point (Robinson & Oldham, 2016). Generational shifts in what is considered normal will also impact the BSS category selected because BSS is subjective. Surveys of Americans in 1994 and 2004 demonstrated that the average weight had increased along with visual size, but respondents still classed themselves as normal (Ogden et al., 2006). BSS shows moderate correlation with objectively measured BMI for normal and overweight categories but is poorly correlated for the underweight and obese category (Shiely & Millar, 2021).

New BMI (height exponent of 2.5)

A recent formula for BMI using a height exponent of 2.5 was proposed as an alternative index in 2013 by Nick Trefethen, a mathematician from the University of Oxford in the UK who recognised that one number could not be relied upon to predict something as complicated as the human form (Trefethen, 2013. de Saint-Genoisstraat. 2021). Trefethen considered BMI as ill-founded, stating, "Millions of short people think they are thinner than they are, and millions of tall people think they are fatter" (Trefethen, 2013). New BMI is calculated by multiplying body mass in kg by 1.3 (the square root of 1.69, which Trefethen considered the average adult height) and dividing the result by height to the power 2.5, which effectively makes the BMI unchanged for an average-height adult, enabling use of the current norm charts.

Trefethen showed that using the height exponent of 2.5 would reduce the BMI of a 1.83m person by 1 and increase the BMI for a 1.52m person by 1, which would make a difference for millions of people by categorising them more accurately and providing a better indication of the associated health risks. New BMI uses the same units as BMI, the average height is in metres and so the overall units of New BMI are kg/m^3, the units of density and in a study on a sample of young Filipino adults, both significantly predict percentage body fat (%BF). The study agreed with Trefethen, supporting his findings that participants shorter than 1.69m changed weight classification (Van Haute et al., 2020). However, like BMI, New BMI does not account for gender, age, ethnicity, and body composition and does not distinguish between fat and lean muscle mass (Van Haute et al., 2020).

Strengths and Limitations of BMI

Critically looking at BMI, its poor accuracy of fat mass assessment, its relationship between weight and health, and its role as a determinant of an individual's current health status highlight BMI's limitations and fallibility as a predictive diagnostic tool (Tomiyama et al., 2016). To determine an individual's health risks, BMI does not provide a high enough predictive ability (Dhurandhar, 2016). Since the introduction of BMI nearly 2 two centuries ago, medical, and technological advancements should have made BMI redundant. New body fat assessment methods have been introduced, including DXA, CT, and BIA while computers and calculation programmes for many variations of BMI are abundant. However, despite the limitations of BMI as a measure, it has clear population links to health outcomes, especially the relationship of a high BMI with elevated mortality risk (Gutin, 2018) and medical assessments still rely on Quetelet's original calculation of BMI essentially because it requires simple measurements and is a quick, easy calculation (Burkhauser & Cawley, 2008). BMI is associated with but is not a direct measure of body fat and so is still useful in screening for obesity on a population level (Callahan et al., 2023). The limitations of BMI discussed below outweigh its few strengths and highlight why BMI needs to be improved or replaced. However, the positive aspects of BMI need to be maintained and its popularity as a measure proffers the exploration of a more accurate index and necessitates the continued existence of a comparable time-proven formula.

Muscle vs Fat

Excess body fat is associated with many risk factors for poor health (Burkhauser & Cawley, 2008) and health status affects how we behave and interact in our environment (Culyer & Newhouse, 2000). The most recognised limitation of BMI is that it does not distinguish the proportions of fat and muscle that make up body mass. Caution should be observed when using BMI as an indicator of overweight and obesity because, while body composition can be highly variable, particularly in older and younger people and sportsmen and women, people of the same height and weight will have the same BMI (Kok et al., 2004; Nevill et al., 2006). A study of mainly white Australians of European descent used data from 53 women and 88 men to examine the limitations of BMI in predicting obesity and body composition. Bioimpedance Analysis (BIA) was used to estimate body fat percentage, which indicated that the BMI obesity criterion (BMI = 30 kg/m^2) was equivalent to 25% body fat in men and 30% in women (Frankenfield et al., 2001). The study concluded that all subjects who were obese by BMI were also obese by BIA. However, 30% of the men and 46% of the women who had a BMI below 30 were misclassified as obese based on the BMI criterion.

Age and Sex

A multivariate analysis in one study demonstrated that gender and age accounted for more significant variance in body fat than BMI and concluded that the relationship between BMI and percentage body fat is not independent of age and gender (Jackson et al., 2002). Research shows that, with increasing age, body composition changes; muscle mass is lost and fat mass increases for both genders (Keller et al., 2014), which is not reflected in BMI. Consequently, the relationship between body fat percentage and BMI is sex and age-dependent because of the differences in body composition between males and females and the age-related increase in body fat mass and decrease in fat-free mass (Forbes & Forbes, 1987).

BMI is less accurate at estimating body fat in men than women (Burkhauser & Cawley, 2008) and is considered a particularly poor indicator for men with a BMI of less than 25 kg/m^2 (Meeuwsen et al., 2010). Women generally are shorter than men, have a higher proportion of fat and a lower proportion of muscle, so they tend to have a higher BMI than men of the same weight. Consequently, BMI does not distinguish between men and women of similar height and weight. For example, two people 1.8m tall and weighing 100kg, one with a waist measurement of 120cm and the other with a waist measurement of 96cm, will have the same BMI (30.86, borderline obesity). However, their proportions of fat to muscle will be very different, as will their body shape, a factor missed by BMI. *Figure 1* illustrates that BMI does not discriminate between 5158 men and women from the population of New Zealand Corrections of similar size and weight but substantially different body composition, which was endorsed by similar findings in a study of Sri Lankan adults (Ranasinghe et al., 2013).

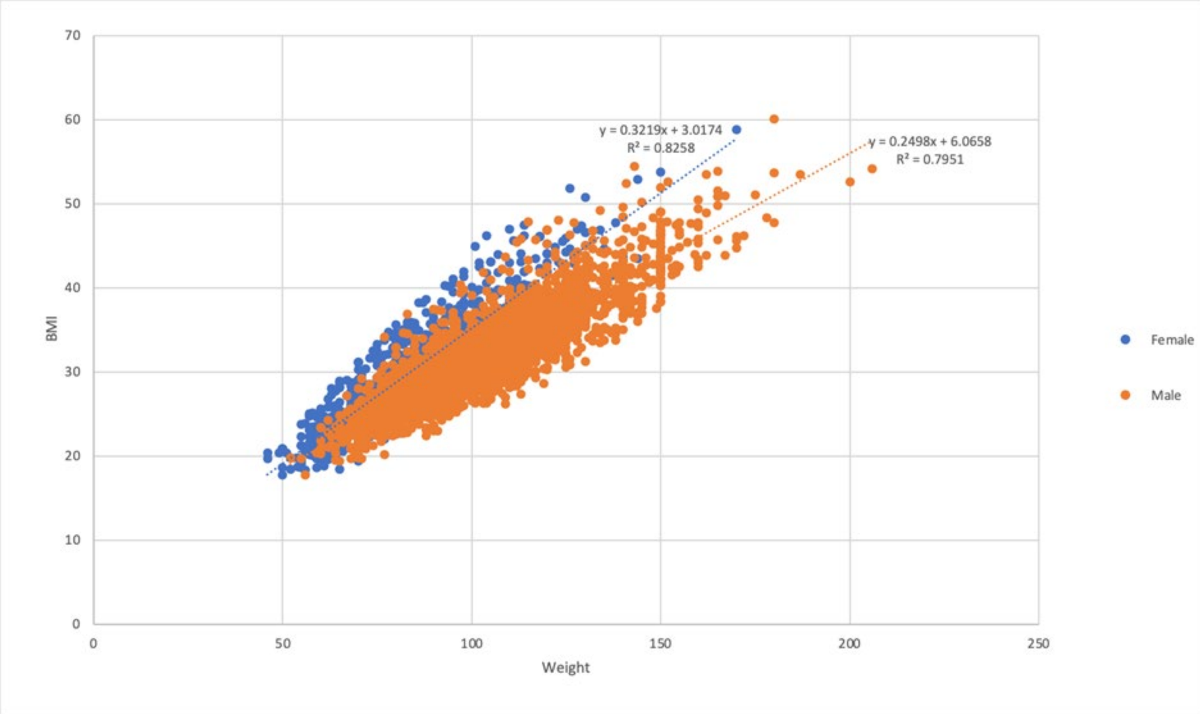

Figure 1:BMI vs Weight for a sample of 1176 women and 3982 men drawn from the population of New Zealand Corrections Officers. (From Walmsley, 2021, unpublished data)

International variations/ethnicity

Research into the appropriateness of BMI as a predictor of health issues and as an estimator of fat percentage across populations is widespread. BMI varies significantly across race/ethnic groups (Heymsfield et al., 2016). One study demonstrated that high body fat increases the risk for disease not high body mass or high BMI, suggesting there may be ethnic differences in the relationship between body fat and BMI (Deurenberg et al., 1998).

Numerous studies across many populations and ethnicities produce mixed results comparing BMI to body fat percentages and indicate significant differences between men and women of different race (Deurenberg et al., 1998; Hsu et al., 2012; Wagner & Heyward, 2000). A study into how the relationship between BMI and body fatness was effected by ethnicity with a cohort of 706 black and white men and women aged 20-94 years concluded that there was no significant difference (Gallagher et al., 1996). However, another study suggests that differences in BMI can occur among populations of the same age, gender, and body fat percentage (Deurenberg et al., 1998). These conflicting results suggest that BMI may not be a universally accurate indicator of body fatness and that individual characteristics and demographic factors must be considered for a more accurate assessment.

The evolutionary adaptations of Polynesian populations, including Pacific Islanders and Māori, enhance their ability to conserve heat in open oceanic environments, characterized by increased body mass (Houghton, 1990), this contributes to the inaccuracy of using BMI to indicate body fat in these groups. Polynesians tend to have higher body mass and larger muscle circumferences, such as upper arms and calves, compared to other ethnic groups (Rush et al., 2009; Stini, 1975). This muscularity and lean body mass lead to greater overall weight, which can cause BMI to inaccurately categorize them as overweight or obese. Polynesians often have lower body fat percentages and higher lean mass compared to Western populations (Lourie, 1972), making BMI a misleading indicator of health risks for this group. BMI fails to account for the unique body composition of Polynesians, highlighting the need for a more accurate measurement of body fat, especially for populations with distinctive physiological traits.

In a study of girls from five different ethnic groups, South Asian and East Asian girls had significantly higher body fat levels at a fixed BMI and age than European, Māori and Pacific Island girls (Duncan et al., 2009), which is in line with previous investigations (Lourie, 1972). The body composition of Asian populations was characterised by higher body fat, a slender frame and low muscularity. In contrast, Pacific Island people had greater muscle mass, bone mineral density and presented the lowest percentage body fat for a given BMI of all five ethnicities (Lourie, 1972). When calculating BMI for the Polynesian phenotype, lean tissue may be mistaken for fat mass because Polynesians are often tall, muscular, and large in stature causing incorrect categorisation as obese.

There are notably significant ethnic differences between populations (Keys et al., 2014). In a sample of New Zealanders of Māori, European, Pacific Island, and Asian Indian descent, there were marked differences in body shape, composition, and fat distribution (Rush et al., 2009). The difference was most pronounced between people of European and Asian Indian descent, the latter having higher total and central fat levels that increased specifically in the abdominal region with increased age (Deurenberg-Yap et al., 2000; Rush et al., 2009). New Zealand has an increasingly diverse population because of immigration and Asian Indians are a rapidly increasingly section of the population with body composition characteristics that distinguishes them from other Asian sub-groups (Tan, 2004).

From a broader viewpoint, adopting region-specific and ethnicity-specific assessment criteria could enhance the accuracy of health evaluations and interventions. A one-size-fits-all approach may overlook critical nuances, potentially leading to misdiagnosis or inappropriate health recommendations. Incorporating tailored anthropometric measurements into indices of body composition could reduce health disparities by providing a more equitable framework for assessing and addressing the unique health needs of various ethnic groups. As global populations become increasingly diverse, such nuanced approaches will likely become essential in advancing public health strategies and medical research ensuring they are more inclusive and representative of diverse populations. Public health policymakers should recognise the distinction between ethnic groups to reflect a better assessment of health (Rush et al., 2009).

Relationship to Health

Numerous studies have investigated the relationship between BMI and various health outcomes (Frank et al., 2019; Pi-Sunyer, 2002) and suggest that higher BMI is associated with an increased risk of a variety of health conditions, including type-2 diabetes, cardiovascular disease, and some types of cancer. Additionally, higher BMI has been linked to decreased life expectancy, although some research has suggested that the relationship between BMI and health outcomes may not be straightforward (Walls et al., 2012). For example, two studies found that individuals with a high BMI may be at lower risk for certain health conditions, such as osteoporosis and some types of infections because BMI cannot discriminate between individuals of the same mass and stature but substantially different body composition (Ha & Baek, 2020; Hariri et al., 2019).

While existing literature suggests that BMI is useful for assessing populations and predicting specific health outcomes, it is pertinent to also consider the limitations of BMI as a health indicator and to use it in conjunction with other indicators of health for individuals (Jackson et al., 2002). The health impact of body fatness is particularly troubling because within the Organisation for Economic Co-operation and Development (OECD) countries, New Zealand has the third highest rate of obesity for both adults and children, with 30% of the adult population classed as obese (Utter et al., 2015). Given the link between fatness and morbidity and mortality, excessive fatness is now recognised as one of the most severe public health challenges facing the OECD and other industrialised countries (James et al., 2004; Utter et al., 2015). Misclassifying obesity using BMI can significantly affect health, as it may lead to missed opportunities for accurate diagnosis and early intervention, potentially resulting in preventable morbidity.

Before high body mass was linked to medical issues, historically and culturally, corpulence was considered healthy, desirable, and a sign of wealth (Jutel, 2009). However, the fashion industry and commercial advertising, reinforced by social media, have skewed perceptions of the norm. Even young women who fall into the normal and underweight category of BMI view themselves as too fat (Nuttall, 2015). Societal biases and stigma negatively affect both physical and mental health, fuelling discrimination and distorting individuals' perceptions of their bodies. To reduce these issues, a new method is needed, one that accurately reflects body composition without categorizing people. This would help minimize discrimination and lessen the impact of societal perceptions on what is considered a "normal" body shape, ultimately improving health outcomes. As demographics shift, regional variations emerge, and our understanding of body composition becomes more diverse, the limitations of BMI become increasingly clear.

Anthropometric approaches to estimating fat mass

Anthropometric measurements like weight, height, girths, and skinfold thickness have been used to assess size, shape and body composition. Anthropometric indices derive from anthropometric measurements that are combined with each other or additionally with other information. These indices, like BMI, PI and WTHR, can be used to make interpretations about growth, development, and body composition. There are a variety of standardised protocols for the measurement of anthropometric dimensions (Bray, 2014) that are necessary for accuracy and consistency. Two internationally recognised protocols used frequently in sport and wellness studies were chosen for this research. The International Society for the Advancement of Kinanthropometry (ISAK) protocol was used for skinfolds because it is an international standard for anthropometric assessment (Marfell-Jones et al., 2012; Marfell-Jones et al., 2006). The American College of Sports Medicine (ACSM) protocol was used for height, weight, waist and hip girths because the ACSM Guidelines for Exercise Testing and Prescription have been a fundamental resource for exercise professionals since 1975 (Lippincott williams & wilkins, 2013; Norton & Eston, 2019).

Imaging approaches to estimating body fat.

Different methods to estimate body fat have been investigated in a variety of studies (Jebb, 1999; Ræder et al., 2018). The most accurate means of estimating body fat are underwater weighing, dual-energy x-ray absorptiometry (DXA), Computed tomography (CT), and magnetic resonance imaging (MRI). However, these methods are often not readily available, are expensive and need to be conducted by highly trained personnel (Nuttall, 2015). Furthermore, many of these methods can be difficult to standardise across operators or machines, which can cause difficulties drawing comparisons across studies and time periods. However, Bio-electrical Impedance Analysis (BIA) is simple, easily accessible, and an inexpensive practical measurement, which has been found to have strong correlations to DXA for measuring fat mass (Sluyter et al., 2011; Thomson et al., 2007). DXA is often cited as the gold standard measure for fat mass (González-Ruíz et al., 2018; Jebb, 1999; Ræder et al., 2018).

BIA is a not a new method of estimating body fat percentage (Kyle et al., 2004), but it has gained more recognition in recent years with a significant increase in research around its accuracy (Mialich et al., 2014). Between 1990 and 2003 over 1600 research papers about BIA were published in English medical journals (Kyle et al., 2004). Research illustrates that any body composition estimate demonstrably superior to BMI in predicting health risks is particularly important (Meeuwsen et al., 2010). For example, a Swedish study showed that body fat estimated by BIA was a better predictor of mortality than BMI in women aged 45–75 years (Böhm & Heitmann, 2013). Furthermore, a study comparing DXA and BIA to estimate body fat in 591 healthy subjects from Newfoundland and Labrador concluded that BIA is a good alternative for estimating body fat percentage when subjects are within a normal body fat range (Sun et al., 2005). However, the same study noted that BIA may underestimate body fat percentage in obese subjects and overestimate it in lean subjects. An additional study found BIA to be an accurate method for estimating Fat Mass (FM) and Fat Free Mass (FFM) both of which are associated with morbidity and mortality (Böhm & Heitmann, 2013).

BIA does have limitations related to age, disease, and ethnicity. For example, increased age has been associated with decreased hydration and conditions such as cardiovascular disease and oedema can impact cellular fluid levels. Because BIA relies on total body water estimations for its assessment of fat mass, the error in fat mass estimation by BIA may increase with age (Böhm & Heitmann, 2013). Differing races and ethnicities with disparities in limb length, body size and structure may also introduce errors into estimation of body fat by BIA (Deurenberg & Deurenberg-Yap, 2003). Despite its limitations BIA is simple to use and has been shown to provide a useful indication of body composition by estimating FFM, FM, and Total Body Water (TBW) and so is a suitable approach for the estimation of fat mass for the general population (Böhm & Heitmann, 2013). BIA was chosen as the criterion measure for %BF in this study due to its convenience and validity (Jebb, 1999; Kyle et al., 2004; Nuttall, 2015). While skinfold thickness measurements were taken, they were ultimately not used as the criterion measure. Consistent with previous research, the challenges in obtaining accurate and reproducible skinfold measurements particularly in very obese individuals led to their exclusion from consideration as the primary method for assessing %BF (Bray & Popkin, 1998; Chumlea et al., 2002; Mei et al., 2002).

Chapter 3 Methodology

Design

A cross-sectional observational design was adopted from an opportunity sample including the general public, Corrections Officers, and members from several gyms.

Participants

Consultation with an AUT statistics advisor resulted in a decision to recruit a sample with no upper limit. The final sample size reflects the time and resources appropriate for a masters level research study. A convenience sample was recruited from the New Zealand general population. All participants were from Auckland, including both male and female, a variety of ages, health backgrounds and ethnicities from the four main categories: Māori, European, Asian and Pacific Island.

All participants were at least 18 years old with no maximum age limit. Exclusion criteria were participants who indicated a pacemaker, oedema or abnormal tissue hydration, chronic metabolic syndrome, or cardiovascular disease on medical screening. Participants gave written consent to have anthropometric measures taken and completed a medical screening form that included consent to stand on a BIA machine, allowing a low electrical signal through the body. Ethical approval for research was granted by AUT on the 27th of January 2023 under the reference 22/384.

Protocols

To ensure reliability all participants received an information sheet before their appointment outlining pre-testing guidelines as well as details on the location, time, and duration of the appointment. The information sheet requested that in the 24 hours prior to testing, participants avoided vigorous exercise, consumed no alcohol, got their regular sleep of 6-8 hours, consumed their regular food intake and maintained normal hydration. Although requested, participants' adherence to these guidelines were not monitored or enforced.

Participants attended a single 25-minute appointment, which comprised approximately ten minutes of completing forms while standing and fifteen minutes of passive anthropometric testing. Participants were invited to read and discuss the information sheet, ask questions, and complete the medical screening form and written informed consent, which included the consent for BIA. Participants were then asked to change, if necessary, into shorts, a t-shirt, and suitable underwear (no underwired bras). All anthropometric testing was completed barefoot. Scheduled appointments all took place in the afternoons between twelve and five pm for improved clinical application and standard methodology (Kyle et al., 2004).

Data Collection

The anthropometric passive assessments of height, mass waist girth, and hip girth followed ACSM's guidelines for Exercise Testing and Prescription, 10th edition (Medicine, 2013b). Height was measured with a stadiometer in a standing position, feet together without footwear to the nearest 0.1cm. Mass was measured on the Tanita BC 420MA Body Composition Analyser (BIA) feet hip width apart, standing upright with arms alongside the body to the nearest 0.1kg. Waist and hip girths were measured with feet together with normal breathing at the identified narrowest and widest points to the nearest 0.1cm. Eight skinfolds were measured on the left side of the body, locations were marked and checked following the ISAK guidelines *Figure 2* (Marfell-Jones et al., 2012). Measurements were taken using Harpenden callipers at the bicep, triceps, sub-scapular, iliac, supraspinale, abdominals, mid-thigh, and medial calf sites to the nearest 1mm. Skinfold measures were taken twice at each site and only if the result deviated by ten percent was a third measurement taken. The same tester conducted all assessments, and a female tester was on hand if requested by participants. Testers were ACSM accredited and ISAK trained but not accredited.

Figure 2:Skinfold site measurement points, Triceps, Bicep, Subscapular, iliac, Supraspinale, Abdominals, Mid-Thigh, Medial Calf and Harpenden Callipers. (Images are still shots from the video on YouTube of the official ISAK manual 2019).

The BIA device used for testing was pre-programmed to 0.5 kg to account for the average weight of light clothing before body mass was measured. Participants stood quietly on the BIA device with all contact areas cleaned before connection with the machine. Height, gender and age were entered into the BIA device. Participant results were recorded following a standardised 10-minute standing period (form filling time) to minimise acute shifts in fluid distribution, improving the validity of results (Chugh, 2004). During the measurement, the instrument recorded whole body impedance by applying an electric alternating current of 90 μA at an operating frequency of 50 kHz. Percentage body fat (%BF) was calculated by the BIA device from the whole-body impedance value and the variables height, weight, gender, and age. %BF was estimated to the nearest 0.1% using standard equations provided by Tanita the BIA manufacturer.

Data collected from the BIA (weight, fat percentage and water percentage) in addition to all passive anthropometric measures (height, waist/hip girths, skinfolds, subscapular, triceps, biceps, supraspinale, iliac, abdominal, mid-thigh, medial calf) and personal metrics (age, ethnicity, sex) were entered into an Excel spreadsheet. Each participant was given a unique identifier (UID) to comply with anonymity.

Data Analysis

All data were checked, and any errors corrected. Height and weight measurements were used to calculate BMI (weight/height^2, kg/m^2) and compared to categories of BMI developed by the WHO. the waist and hip girth measurements were used to determine Waist to Hip Ratio (WHR), (waist circumference/hip circumference, cm).

Statistical Analysis

IBM SPSS Statistics version 29.0 (SPSS, Inc., Chicago, IL, USA) was used in the analysis. Descriptive statistics grouped by gender (male and female) and ethnicity (NZ European, Māori, Pacific Island and Asian) were determined.

Prior to regression analyses preliminary analyses ensured that the assumptions regarding sample size, normality, linearity, heteroscedasticity, autocorrelation, outliers/leverage points and multicollinearity of correlated independent variables were valid. The subscapular and supraspinale variables were excluded from regression analyses because they showed a high collinearity >10. Cohens f was used to estimate the effect size between variables as small (d = 0.2), medium (d = 0.5), and large (d ≥ 0.8) (Cohen, 1988).

Regression analyses were undertaken to investigate the relationship between %BF and anthropometric variables for male and female sub-groups. Regression outputs indicated the extent to which the independent variables explained variance in the dependent variable(s) and the standardised beta coefficient (*β)* indicated the magnitude of the effect of each independent predictor variable.

Stepwise regressions were carried out for males and females using the most significant predictors of fat mass from the regression findings. The strongest predictors identified with the largest standardized regression coefficient were used to explore the development of a novel index. Bi-variate Pearson's correlations informed analysis of the relationships between %BF and BMI. Subsequent bi-variate Pearson's correlations were run to check the relationship between %BF and a novel index for sub-groups defined by ethnicity and gender.

Finally, linear regression analysis compared the variance in body fat for BMI, the Ponderal Index, Waist to Hip Ratio, New BMI exponent 2.5, and a novel index to predict the value of the relationship R and R^2.

Chapter 4 Results

Demographics

A total of 99 adults, 50 females and 49 males, were examined during the study. The study sample represented the four main ethnic groups in New Zealand made up from 35 New Zealand European (NZE), 25 Asian, 21 Pacific Island and 18 Māori. Ages ranged from 19-73 years (mean: 42.5 ± 12.7 years). Participant height ranged from 1.41m to 1.98m, mass ranged from 49.1 to 164.4 kg, body fat percentage values ranged from 8% to 51% (mean: 35.4 ±9.07%), BMI values ranged from 17.1 to 46.5 (mean: 29.2 ±6.26). *Table 4* gives the descriptive statistics for male and female subjects contrasted by ethnicity and shows the anthropometric and body composition gender differences. Males were significantly taller, heavier, and had lower %BF than females. The descriptive statistics show that male and female Pacific Island participants were significantly heavier than NZ European, Māori, and Asian participants ($P<0.05$), as previously detailed. Pacific Island people had the greatest waist girths and %BF, and, in contrast, Asian participants had the smallest frame but the lowest body fat of all ethnicities.

Table 4:Anthropometrics of male and female grouped by ethnicity. Data are mean ± SD

	Males (n= 49)				Females (n= 50)			
Measurement	NZE (n=12)	Māori (n=9)	Asian (n=13)	Pacific Island (n=15)	NZE (n=23)	Māori (n=9)	Asian (n=12)	Pacific Island (n=6)
Body Fat %	(25.4 ± 9.61)	(25.1 ± 8.98)	(24.3 ± 4.68)	(29.1 ± 5.91)	(33.8 ± 9.72)	(36.2 ± 10.2)	(31.3 ± 5.97)	(40.5 ± 4.32)
Height in m	(1.83 ± .064)	(1.79 ± .067)	(1.77 ± .084)	(1.82 ± .077)	(1.60 ± .077)	(1.60 ± .094)	(1.60 ± .099)	(1.63 ± .073)
Mass in kg	(97.2 ± 21.6)	(96.6 ± 29.0)	(87.6 ± 13.9)	(114 ± 18.2)	(74.1 ± 18.1)	(76.9 ± 13.6)	(65.1 ± 7.22)	(82.3 ± 16.6)
Waist girth in cm	(95.8 ± 13.9)	(98.4 ± 17.9)	(95.8 ± 9.95)	(109 ± 13.8)	(86.5 ± 13.4)	(92.0 ± 13.3)	(83.8 ± 11.1)	(89.0 ± 10.1)
Hips girth in cm	(108 ± 13.3)	(109 ± 9.19)	(102 ± 6.09)	(117 ± 8.44)	(106 ± 12.8)	(109 ± 12.2)	(103 ± 12.6)	(109 ± 11.0)
Subscapular in mm	(25.1 ± 11.5)	(24.8 ± 18.3)	(29.2 ± 8.1)	(32.9 ± 13.9)	(22.8 ± 7.6)	(27.8 ± 9.5)	(30.9 ± 10.1)	(33.8 ± 9.0)
Triceps in mm	(16.1 ± 8.7)	(10.1 ± 3.8)	(12.2 ± 2.8)	(14.1 ± 4.1)	(22.4 ± 6.3)	(22.7 ± 9.4)	(25.0 ± 7.6)	(26.0 ± 4.0)
Bicep in mm	(9.1 ± 5.0)	(6.9 ± 2.0)	(7.9 ± 2.1)	(10.0 ± 3.9)	(12.6 ± 5.5)	(12.2 ± 4.8)	(13.3 ± 4.7)	(15.3 ± 3.3)
iliac in mm	(19.1 ± 12.3)	(17.1 ± 9.5)	(18.3 ± 5.4)	(21.3 ± 7.5)	(19.2 ± 7.07)	(21.4 ± 8.7)	(20.3 ± 6.5)	(23.5 ± 6.8)
Supraspinale in mm	(19.8 ± 12.7)	(16.9 ± 9.2)	(19.2 ± 5.2)	(21.1 ± 8.6)	(18.4 ± 7.6)	(22.1 ± 8.7)	(20.1 ± 7.1)	(23.7 ± 6.1)
Abdominals in mm	(27.8 ± 18.2)	(20.8 ± 13.2)	(23.2 ± 6.2)	(29.6 ± 10.5)	(24.1 ± 8.6)	(29.3 ± 9.9)	(25.8 ± 9.9)	(27.5 ± 9.2)
Mid-Thigh in mm	(23.3 ± 8.4)	(18.7 ± 4.9)	(19.9 ± 4.2)	(19.7 ± 4.8)	(29.0 ± 7.6)	(26.7 ± 10.4)	(28.0 ± 6.1)	(26.0 ± 4.7)
Medial Calf in mm	(16.6 ± 7.9)	(11.3 ± 3.9)	(13.1 ± 4.8)	(13.3 ± 3.1)	(18.4 ± 5.2)	(18.9 ± 8.2)	(17.6 ± 3.3)	(18.8 ± 2.0)

NZE = New Zealand European

Subscapular, Triceps, Biceps, iliac, Supraspinale, Abdominals, Mid- Thigh and Medial Calf are all skinfold measurements.

Table 5 shows categories of BMI for sex and ethnicity. From the sample 4 participants had a BMI <19.9 (underweight), 22 from 20-24.9 (normal), 31 from 25-29.9 (overweight-pre-obese), and 42 had BMI above 30 (obese) broken down into class I (n=25), class II (n=11) and class III (n=6).

Table 5:Categories of BMI for sex and ethnicity

BMI Category	**Female**				**Male**			
	NZE	Māori	Asian	Pacific Island	NZE	Māori	Asian	Pacific Island
Underweight	2	1	0	0	1	0	0	0
Normal	10	1	8	0	1	1	1	0
Overweight	3	1	1	3	5	6	10	2
Obese	8	6	3	3	5	2	2	13
Total	23	9	12	6	12	9	13	15

Male and Female anthropometric measurement comparisons

A linear regression analysis with the independent variables height, weight, waist girth, hip girth, triceps, bicep, iliac, abdominals, mid-thigh, and medial calf skinfold thicknesses, and age explained 80.7% of the variance in percentage body fat for the entire cohort (F (13,85) = 27.328, p<.001, r^2 = 0.807). When considering males only, the same independent variables explained 82.8% of the variance in percentage body fat (F (13,35) = 12.964, p<.001, r^2 = 0.828). When considering females, the same independent variables explained 89.4% of the variance in percentage body fat (F (13,36) = 23.333, p<.001, r^2 = 0.894). There was a statistically significant difference in anthropometric measurements based on being either male or female and a large effect, (*F* (13, 85.0) = 35.96, *p* < .001; Wilk's λ = 0.150, partial η^2 = 0.85).

A stepwise regression was conducted for females with the dependent variable bodyfat and model 3 was chosen with weight, height, and triceps skinfold thickness as the predictors. The results showed the utility of the predictive model was significant, (F (3,46) = 110.899, p<.001. R^2 = .879) which explains 87.9% of the variance in body fat, less than 2% different to the model for females with all 11 independent variables. Mass made the largest unique contribution with 58.9%, height contributed 18.5%, and triceps skinfold thickness the least with 10.5%. A stepwise regression for males revealed the independent variables weight, waist girth and triceps skinfold thickness were significant predictors of %BF (F (3,45) = 50.560, p<.001) explaining 77.1% of the variance in %BF, less than 6% different to the model for males with all 11 independent variables. Mass made the largest unique contribution with 23%, waist girth contributed 22.2%, and triceps skinfold thickness the least with 9.6%.

Exploring a new index

The exploration of a novel body fat index focused on integrating a shape measurement, which BMI currently lacks, into the equation alongside height and weight. Mass, defined as the amount of matter in an object and measured in kilograms, is generally proportional to volume, assuming density is constant. In humans, body density inversely correlates with the proportion of body fat, as fat proportion increases, average body density decreases. Therefore, an index expressed in units of density should exhibit a strong correlation with %BF.

Through regression analysis, triceps skinfold thickness and waist girth were evaluated for their potential inclusion in the new index. Waist girth emerged as a more appropriate measure, given that individuals with a higher waist-to-hip ratio (WHR) tend to exhibit a greater fat percentage, particularly in the abdominal region. Including waist or hip girth, or WHR, in combination with height and body mass could produce an index with density-based units, which would be more suitable for an indicator of fat mass (Arif et al., 2022).

BMI's primary limitation is its inability to differentiate between muscle mass and fat mass, as it treats all weight equally. Incorporating WHR addresses this issue by providing an additional metric that reflects both body fat distribution and overall body size. To improve on BMI as an estimator of fat, a novel index called the Bodyfat Distribution Index (BDI) was introduced, calculated as body mass divided by height, and then multiplied by WHR. This novel index BDI could offer a more nuanced understanding of body composition and serve as a better indicator of fat distribution and health risk.

A Comparative analysis of traditional fat mass indices and BDI

Linear Regression analysis with %BF as the dependent variable was compared to the current most used indices explored in the literature review, BMI, New BMI exponent 2.5, Waist to Height Ratio (WTHR), the ponderal index (W/H^3) and the novel index BDI to predict the value of the relationship R and R^2 values *Table 6*.

Table 6:R and R^2 values for index of fat mass most researched and the novel index

Index	R	R Square
BDI	.776	.602
W/H^3	.756	.568
NEW BMI EX 2.5	.725	.525
BMI	.669	.447
WTHR	.612	.375

Dependent variable: %BF

BMI and Novel Index BDI Comparisons

A bivariate Pearson correlation was calculated to evaluate the linear relationship between %BF and both BMI and the novel index BDI across the entire cohort, as well as within male and female subgroups *(Table 7)*. The results showed a significant strong positive correlation between BDI and %BF for the entire cohort, males, and females, indicating that body fat percentage increases as BDI increases. Similarly, there was a significant positive correlation between BMI and %BF across all groups, demonstrating that body fat percentage increases with BMI.

Table 7:Relationship between Percentage body fat (%BF) and BMI and %bf and the novel index

	BMI			Novel Index BDI		
Values	**n**	**r**	**p**	**n**	**r**	**p**
Whole Cohort	99	.669	<.001	99	.776	<.001
Males	49	.834	<.001	49	.623	<.001
Females	50	.916	<.001	50	.836	<.001

A scatterplot *Figure 3* shows the significant positive relationship highlighted between BMI and body fat for males and females from BIA. The correlations explains that 45% of the of the variability of body fat can be explained by BMI. Notably *Figure 3* indicates that males and females with the same %BF will have a different BMI.

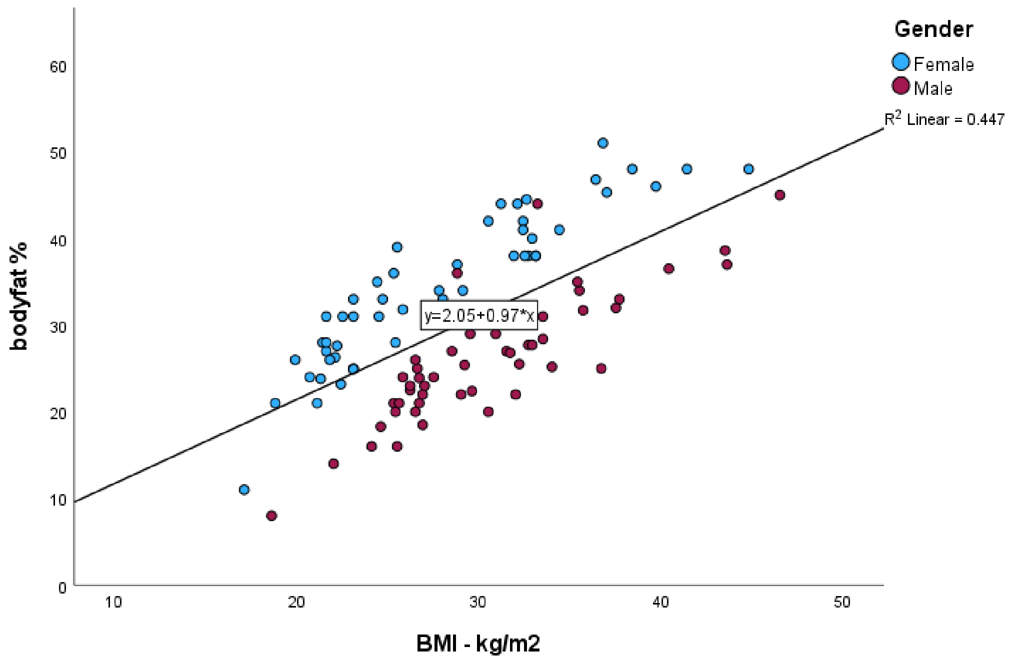

Figure 3:Correlation between percentage body fat and BMI for males and females

A scatterplot *Figure 4* shows the significant positive relationship between BDI and Body fat for males and females and shows that 60% of the variability of body fat can be explained by BDI. Notably in contrast to *Figure 3*, *Figure 4* indicates that females still have greater scores than males for the same %BF, but the sex differences are markedly less than for BMI.

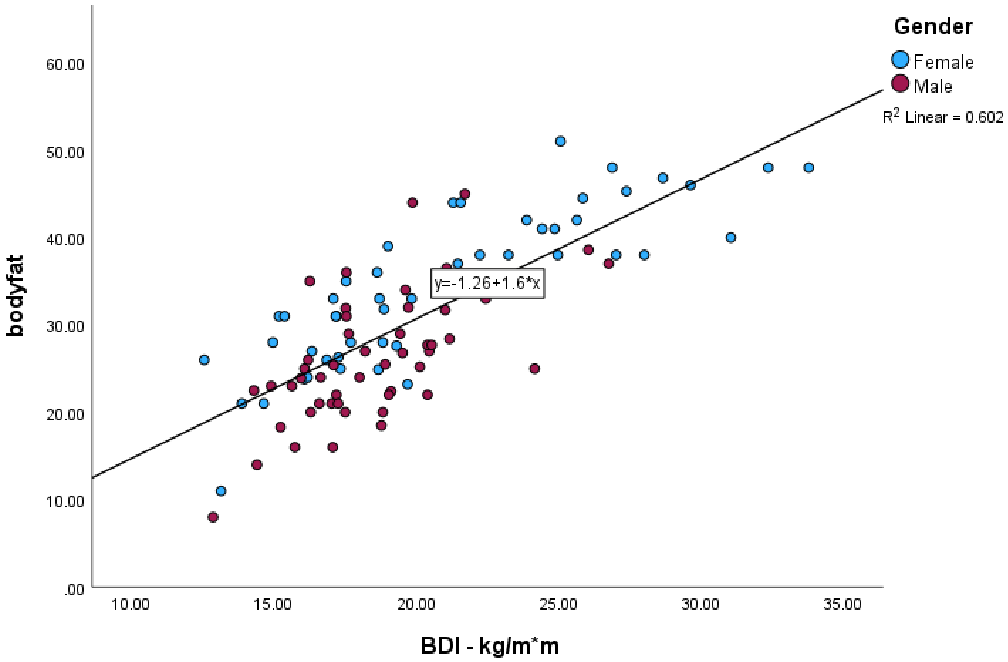

Figure 4:Relationship between percentage body fat and a novel index BDI for males and females.

Ethnicity BMI and the novel index BDI comparisons

The relationship between BMI and %BF shown in *Figure 5* demonstrates that Pacific Island females are substantially different from NZ European, Māori and Asian females. In Pacific Island women, for a unit increase in BMI, %BF increases by 0.56% unlike NZ European, Māori, and Asian women where %BF increases by between 1.14% and 1.44% for each unit increase in BMI.

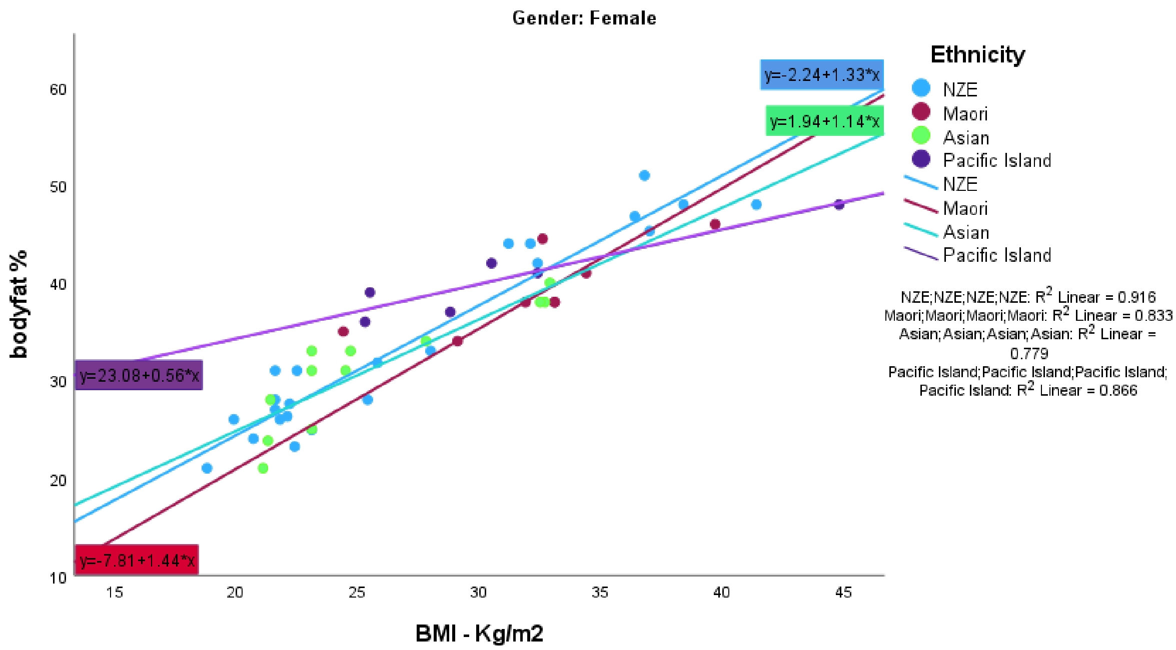

Figure 5:Relationship between body fat percentage and BMI by ethnicity for females

The relationship %BF and BDI the novel index by ethnicity in *Figure 6* suggests that Pacific Island females are grouped with Asians and are substantially different from NZ European and Māori females. For a unit increase in BDI, %BF for Pacific Island women increase by 0.73% and by 0.94% for Asian women. For NZ European and Māori women, a unit increase in BDI increases %BF by 1.62% and 1.81% respectively.

The slope of the lines of best fit in *Figure 5* show that Pacific Island females are the only distinguishable group when looking at the relationship between %BF and BMI by ethnicity. However, *Figure 6* clearly shows that the lines of best fit better distinguish between Pacific Island and Asian women in one group and NZ European and Māori women in another group when looking at the relationship between %BF and BDI by ethnicity.

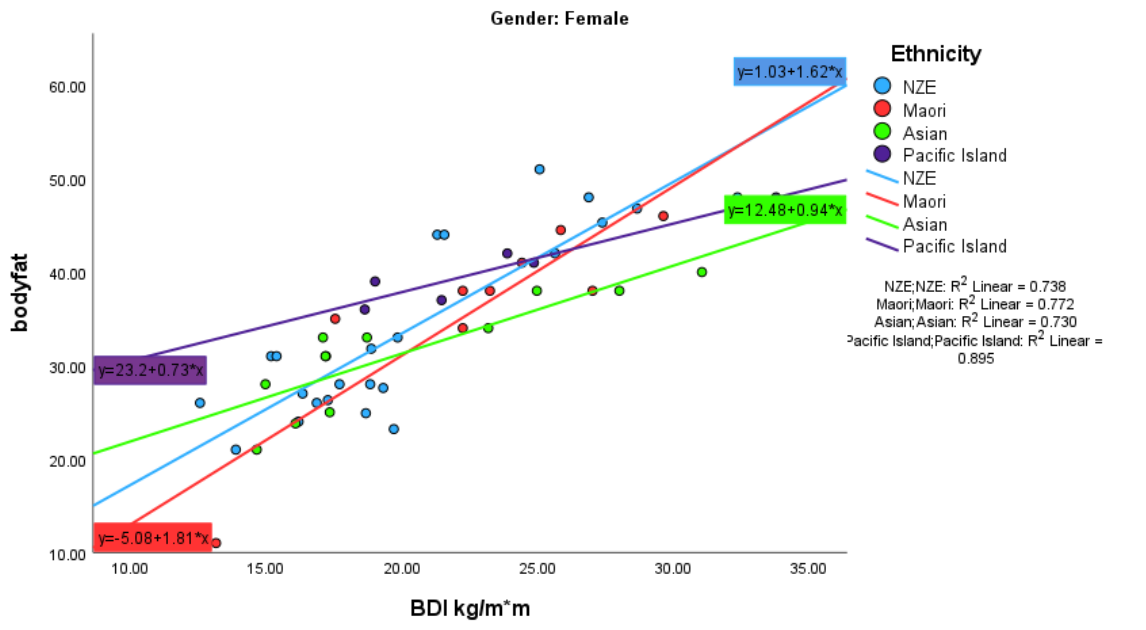

Figure 6:Relationship between bioimpedance derived percentage body fat and the novel index BDI by ethnicity for females (novel index = BDI)

The relationship between %BF and BMI by ethnicity for males shown in *Figure 7* suggests that there is a similar strong relationship for all ethnicities. For a unit increase in BMI, %BF increases by between 0.99% and 1.44%.

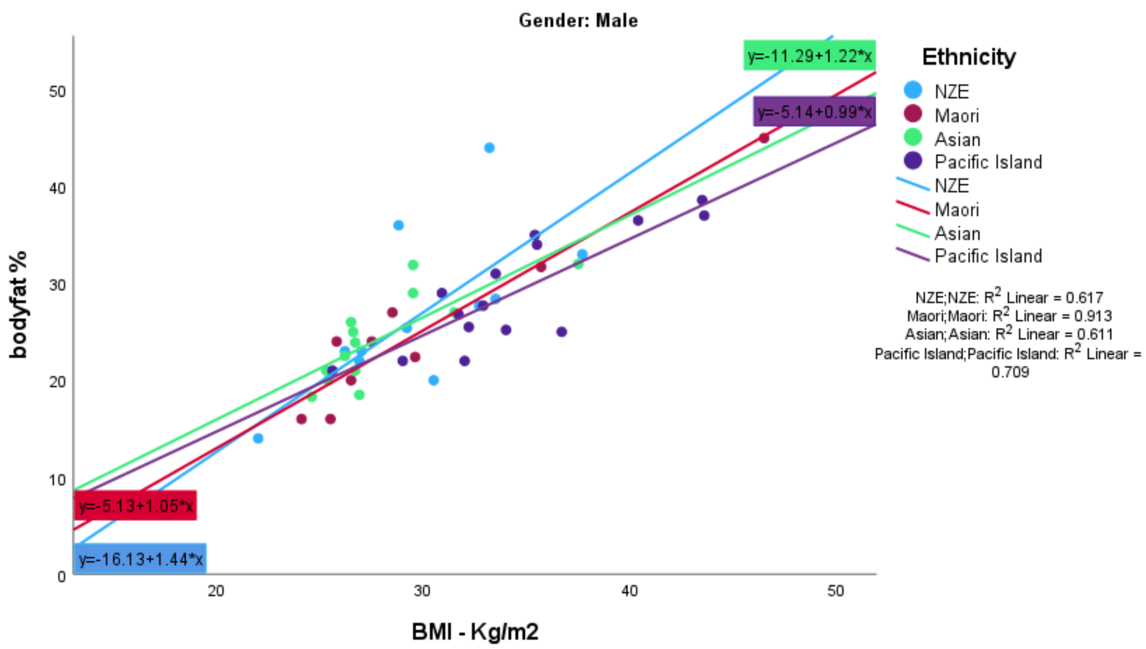

Figure 7:Relationship between body fat percentage and BMI by ethnicity for males

For males *Figure 8* suggests a weak relationship between %BF and BDI for Pacific Islanders and Asians and a moderate to strong relationship for NZ European and Māori. For a unit increase in BDI, %BF increases by 0.8% in Pacific Island men, by 1.5% in Asian men, 2.3% in NZ European men and up to 3.65% in Māori men. The slope of the lines of best fit in *Figure 7* range from 0.99 to 1.44 showing that, in males, there is little difference between ethnicities in the relationship between %BF and BMI. *Figure 8* clearly shows the slopes of the lines of best fit range from 0.8 to 3.65, which better distinguish between ethnicities, particularly between Māori and Pacific Island males in the relationship between %BF and BDI.

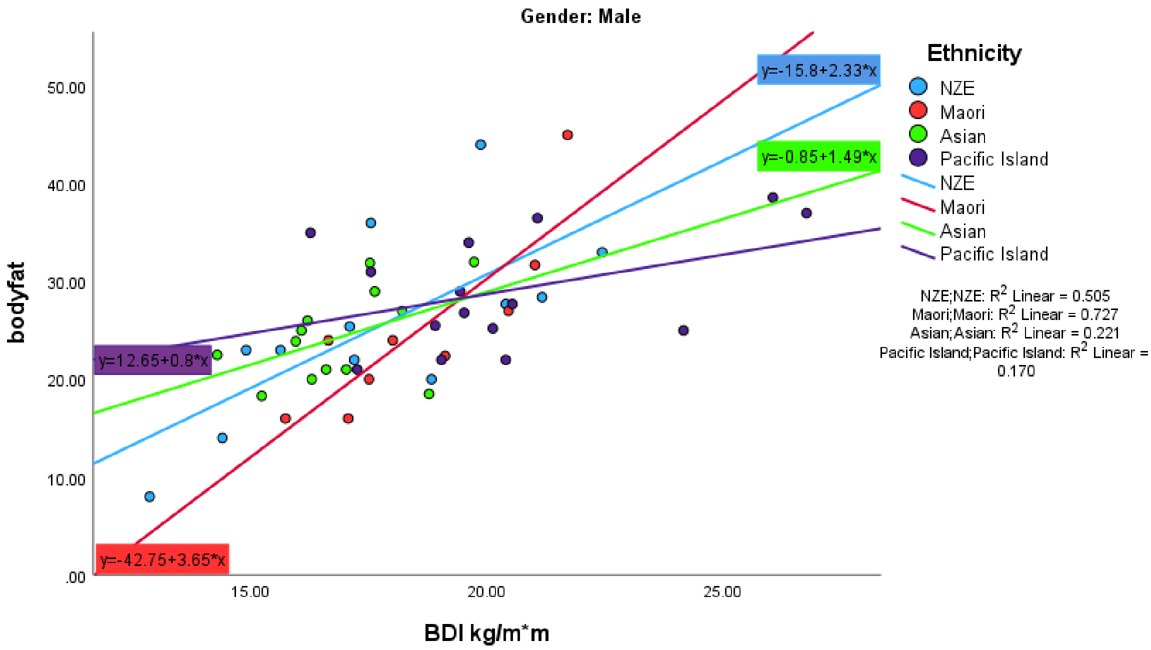

Figure 8:Relationship between percentage body fat and the novel index BDI by ethnicity for males (novel index = BDI)

Chapter 5 Discussion

By 2030 it is estimated that 1 billion people will be living with obesity (World Health Organisation web page). The WHO had hoped to reduce the growing problem by 2025, but the levels of obesity calculated in 2010 are predicted to double by 2030 (World Obesity. WHO, page visit dated 21/11/23). Obesity is currently classified by BMI, which is recognised "as the simplest and most cost-effective option for tracking obesity at the population level" (Prentice & Jebb, 2001). However, the effectiveness of BMI as a true estimator of fat mass is debatable, given its broad application across diverse body types and demographics. This research embarked on exploring the potential of if a simple novel index could surpass BMI as an estimator of fat mass by addressing its limitations. To achieve this, four research questions (RQ) were developed:

RQ1) Does BMI predict fat mass as a percentage of body mass for a sample of the New Zealand population?

Significant strong positive correlations were found between %BF and BMI across the entire cohort and between female and male subgroups (*Table 7)*, demonstrating that %BF increases in accordance with BMI, as reported in previous research (Jackson et al., 2002; Ranasinghe et al., 2013). *Figure 3* illustrates the relationship, indicating that BMI can explain 45% of the variability in %BF and clearly demonstrates a significant difference in body fat percentage between males and females. For the same BMI, women have a higher body fat than men, which aligns with previous research showing that for the same BMI, women had a 10.4% increase in body fat percentage compared to men (Jackson et al., 2002). *Figure 9* showing the estimated marginal means of body fat for participants supports the findings and demonstrates the significant difference between genders. Females have a higher body fat than males which highlights that any index used to measure body fat should have a different value for the same percentage body fat between genders, consequently BMI does not fully account for sex differences in body composition. Therefore, while BMI is a predictor of %BF for a sample of the New Zealand population, it has limitations, especially when comparing across genders.

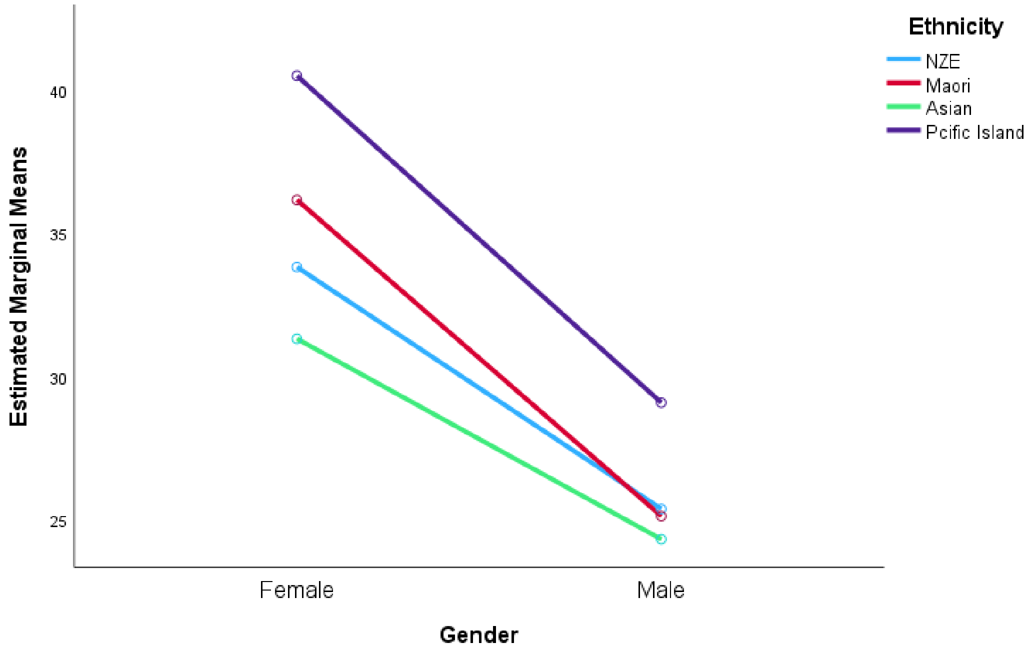

Figure 9:Estimated marginal means of body fat for females and males.

RQ2) Which anthropometric, composition, and personal variables best predict fat mass as a percentage of body mass?

The study utilized linear regression analysis to identify the most effective predictors of %BF for the entire cohort, as well as for males and females separately. For the entire group, height, mass waist and hip girth, skinfold thicknesses (triceps, bicep, subscapular, abdominal, mid-thigh, and medial calf), and age collectively explained 80.7% of the variance in %BF. In gender-specific analyses, waist girth played a prominent role, especially for males, where weight, waist girth, and triceps skinfold thickness explained 77.1% of the variance in %BF. For females, weight, height, and triceps skinfold thickness were the strongest predictors, explaining 87.9% of the variance. In both sexes, weight had the largest unique contribution to %BF, though waist girth stood out as a significant predictor for males.

Research consistently highlights the link between waist circumference and %BF, with studies demonstrating a positive correlation between the two (Arif et al., 2022). Moreover, the EPIC study further emphasizes that the location of fat accumulation particularly around the waist can be a more accurate predictor of health risks than BMI alone (Pischon et al., 2008). This aligns with the current research study findings, where waist girth was a significant predictor of %BF, particularly for men. Abdominal girth measurements are considered a better indicator of health than BMI because abdominal subcutaneous fat is highly correlated with waist circumference (Browning et al., 2010).

Additional research from a study of over 3,000 New Zealand Defence Force personnel, who underwent anthropometric measurements and 3D body scans, found that males generally had larger body dimensions compared to females (Kolose et al., 2021). This supports findings from the current research study, which showed in the descriptive statistics men have greater mean measurements across most variables, except for mid-thigh and medial calf skinfolds, which were higher in females. The differences in fat storage between the sexes, with women storing more fat in the gluteal and thigh regions (gynecoid distribution), may explain these findings (Nuttall, 2015). Notably, the New Zealand Defence Force population is younger and maintains higher fitness standards compared to the general population, which could explain their comparatively smaller waist girths in contrast to the more varied demographic analysed in this thesis (see *Table 8*).

Table 8:Comparison of age and waist girths for a New Zealand General population sample and New Zealand Defence Force personnel

Group		Male (mean ± SD)	Female (mean ± SD)
New Zealand General population sample 2023 (present study)	Age	40.9 ± 14.63	44.79 ± 12.68
	Waist Girth	100.41 ± 14.63	87.14 ± 12.45
New Zealand Defence Force sample 2021	Age	31.6 ± 10.7	30.5 ± 0.4
	Waist Girth	89.8 ± 10.49	80.6 ± 9.49

The descriptive statistics analysis *Table 4* supports existing research statistics for male and female subjects and illustrates the well documented anthropometric differences between genders; males were taller, heavier, and had lower %BF than females (Jackson et al., 2002).

RQ3) Does a novel index incorporating shape better predict fat mass than BMI?

The novel index BDI introduced in this study was found to be a more comprehensive estimator of %BF outperforming BMI. Following analysis of which variables were the most effective predictors of %BF the decision was made to split the cohort into males and females. BDI and BMI were compared to body fat by gender. The scatterplot in *Figure 3* explains that 45% of the variability of body fat by gender was explained by BMI when considering the entire cohort and showed a clear separation of males and females. *Figure 4* shows that 60% of the variability of body fat was explained by BDI when considering the entire cohort. The introduction of BDI is a significantly stronger predictor of %BF and clearly demonstrates it does not separate males from females, and so unlike BMI the novel index can be used for both genders.

The BDI is shown as a significantly stronger predictor of %BF as substantiated in *Table 6*. The five most researched estimators of fat mass in clinical and everyday application, demonstrate that the variability of body fat explained by WTHR is 38%, by BMI 45%, by New BMI exponent 2.5 53%, by W/H^3 57% and that 60% is explained by BDI. The results reveal BDI to be a better indicator of fat mass than the other commonly used indicators for the study cohort. *Table 7* underlines this demonstrating a significant positive correlation between BDI and %BF for the entire cohort, r =.776 <.001 indicating that body fat percentage increases as BDI increases. Similarly, there was a significant positive correlation between BMI and %BF for the entire cohort, r =.669 <.001 demonstrating that body fat percentage increases with BMI. The findings demonstrate a clear picture showing the novel index BDI incorporating WHR, a shape measurement is a stronger and more reliable predictor of %BF than BMI and may therefore be a better indicator of health, making it a better tool for estimating fat mass in diverse populations. Although BDI is a significant improvement on BMI and other common measures there is further scope for improved estimation of %BF.

RQ4) Can a novel index better distinguish between participants of different sex and ethnicity than BMI?

The novel index BDI showed a stronger ability to distinguish between participants of different sex and ethnicity compared to BMI. Figure 4 indicates the relationship between %BF and BDI and shows that although females still have greater scores than males for the same %BF, the sex differences are markedly less than for BMI with data points intermingled and lower Figure 3. Figure 5 and Figure 6 reveal that while BMI did show some differences between ethnic groups, particularly for Pacific Island females, BDI provided clearer distinctions. For example, Pacific Island and Asian females were grouped separately from NZ European and Māori females when using BDI, highlighting its effectiveness in distinguishing between ethnicities. Additionally, for males, BDI showed a greater range of variability between ethnic groups. Figure 7 reveals that BMI does not significantly distinguish between any of the ethnicities, NZE, Māori, Asian, and Pacific Island shown by the small range in the slope lines of best fit from 0.99 – 1.44. The relationship of body fat to BDI in *Figure 8* suggests a weak relationship between Pacific Island and Asians and a moderate to strong relationship between NZE and Māori. The difference can be seen by a noticeably larger range in the slope lines of best fit from 0.8 in Pacific Island people to 3.7 in Māori.

In New Zealanders of Māori, European, Pacific Island, and Asian Indian descent the differences in body shape, composition, and fat distribution confer with previous research (Rush et al., 2009). Additionally research shows the growing population group of Asian Indians in New Zealand should be assessed differently from other Asian sub-groups (Rush et al., 2009), suggesting the need for a move towards more culturally and physiologically relevant standards and future research. Rush notes that the New Zealand Ministry of Health adjusted BMI thresholds to 26kg/m^2 and 32kg/m^2 for overweight and obesity in Māori and Pacific Island adults acknowledging the variations. The findings underline the need for a simple novel index advancing on BDI tailored to account for ethnic differences, which would enhance the accuracy and individual relevance of assessments.

Cohort Demographics

The descriptive statistics analysis from the study supports the need for a novel index to account for the diverse range of ethnicities and gender. *Table 4* shows the descriptive statistics for male and female subjects grouped by ethnicity and shows the centre and spread of the data set provides a good cross section of the population. The descriptive statistics reveal some conflicting results. On average, Asian participants were shorter, lighter and had the lowest body fat of all ethnicities, while Pacific Island participants were the heaviest, had the largest waist girths and the highest body fat percentage. Earlier investigations established that Asian populations had a high-fat body composition profile characterised by a slender frame and low muscularity (Duncan et al., 2009; Lourie, 1972). In contrast, Pacific Island people were tall, muscular, and large in stature (Deurenberg-Yap et al., 2000; Heymsfield et al., 2016). This discrepancy implies that there may have been changes in body composition trends or differences in the populations sampled, highlighting the need for further investigation into the factors influencing these differences and supporting the need for a novel index like BDI that could provide improved body composition estimation across different ethnicities.

The findings showed Pacific Island males had larger mean values in all measurements in general compared to all other ethnicities apart from mid-thigh skinfold, greater in NZE and Asians, and medial calf and triceps skinfolds, which were greater in NZE alone supporting a previous study (Rush et al., 2009). The large mean values of Pacific Island males are supported by *Table 5*, showing that Pacific Island males fall into the BMI obese category more than any other ethnicity. *Table 5* additionally shows that from a random population sample, most participants, 73 out of 99, fall into the overweight/obese categories. This majority indicates a substantial prevalence of these classifications, highlighting either misclassification or potential public health concerns and the need for targeted health interventions and further research. Māori females had larger mean value measurements in all results than NZE females apart from mid-thigh and bicep skinfolds. Pacific Island females had larger anthropometric measurements than all other female ethnicities apart from Māori, who had greater mid-thigh, medial calf, and abdominal skinfolds. This difference in ethnicities underlines research from (Houghton, 1990; Rush et al., 2009), which suggests further research should consider ethnicity in calculations for %BF prediction, especially in females.

Progression of BDI from BMI in a social context

Using an index to classify people into categories like "obese" can be problematic, as it often has negative effects on self-image and self-efficacy. When individuals are told they are obese, it can harm their confidence, making them less likely to engage in activities that could improve their health. Labelling leads to social discrimination, stigma, and shaming, which further compounds the problem, and any new index that similarly categorizes people as "obese" risks perpetuating these issues (Nuttall, 2015).

Research shows that stigma is commonly associated with obesity, leading to widespread discrimination by both individuals and institutions (Carr & Friedman, 2005; Puhl & Heuer, 2009; Spahlholz et al., 2016). This labelled discrimination has significant consequences, contributing to the growing prevalence of obesity and its global health impact. Healthcare professionals often rely on BMI to categorize individuals as underweight, normal weight, overweight, or obese, and then assign health risks accordingly. However, this approach can lead to a narrow, judgmental view of patients, reducing them to their weight category rather than addressing their overall health (Tomiyama et al., 2018). As Saguy and Almeling (Saguy & Almeling, 2008) argue, the media exacerbates this issue by portraying "fat bodies" as diseased, reinforcing the stigma attached to those who do not fall into the "normal" category.

Furthermore, this focus on weight often leads to misdiagnoses, with health complaints being attributed solely to body mass, causing critical aspects of a patient's health to be overlooked. Adults with high BMIs are three times more likely to be denied proper medical care, as their mass becomes the primary focus rather than a more comprehensive assessment of their health (Tomiyama et al., 2018). The BDI could help to alleviate this problem by offering an estimate of body fat percentage, rather than classifying individuals into rigid categories. BDI would provide people with a clearer understanding of their likely body fat levels without labelling them as overweight or obese. This approach avoids the negative psychological and social consequences of being categorized and instead empowers individuals with useful information about their body composition.

Limitations and Future Directions

This study's limitations highlight essential considerations for accurately assessing body composition and developing a body fat index suitable for New Zealand's diverse population. The first limitation involves the inconsistency in waist girth measurement locations. Following ACSM guidelines, waist girth measurements were taken at varied points on the trunk, located at the narrowest point of the waist, which varied especially among overweight participants. Since the narrowest point was often nearer the chest rather than at the umbilicus, these measurements may underestimate waist girth, impacting WHR and body fat distribution accuracy. Larger waist measurements, if consistently taken at the umbilicus, would likely capture greater body fat variability, potentially enhancing the BDI's sensitivity to gender and ethnic differences. Adopting the ISAK procedures for girths will correct this in future research and allow for a more standardized measurement approach, ensuring reliable comparisons and greater accuracy in body fat variability across gender and ethnic groups.

Another methodological limitation arises from the use of BIA as the primary method for body fat estimation. BIA provides a simple, non-invasive, cost-effective, and portable means to measure body fat (Kyle et al., 2004; Nuttall, 2015). However, its reliability hinges on adherence to strict pre-testing guidelines and the use of population-specific predictive equations, which are often not accessible on standard BIA devices, such as the Tanita BC 420MA used in this study. The study did not exclude participants who may not have fully adhered to pre-testing guidelines, which can impact BIA's accuracy. Moreover, BIA relies on general assumptions about total body water content, commonly estimated at 73%, which may vary considerably across ethnicities, genders, and health status (Lohman, 1989; Lukaski, 1996). One study demonstrated inaccuracies in BIA equations for specific ethnic groups, such as NZ Europeans, Māori, Pacific Islanders, and Asians, particularly in younger populations (Sluyter et al., 2011). However, it is not known if BIA is similarly inaccurate for adults in the same ethnic groups. Future research should utilize predictive equations tailored to ethnic groups to improve the accuracy of BIA-derived estimates, aligning body fat assessments more closely with the diverse ethnic backgrounds of New Zealand's population (Kontogianni et al., 2005; Kyle et al., 2004; Sluyter et al., 2011).

An additional limitation is the reliance on self-reported ethnic identity rather than genetic ethnicity, which can obscure distinctions in body composition. For example, New Zealand Europeans and Māori participants reported similar body fat means, potentially due to the limitations of self-identification and current broader categorizations of ethnicity. Future studies should strive to distinguish between self-identified and genetic ethnicity. Further, dividing the general "Asian" classification into Asian and

Asian Indian subgroups would be beneficial, as the Asian Indian population in New Zealand continues to grow and presents unique body composition traits (Rush et al., 2009). Recognizing the ethnic diversity within New Zealand's population would support a more precise approach to health assessment and more accurately reflect the health status of these distinct groups.

The sample size may limit the generalizability of findings. Although the overall cohort was healthy, the smaller and unevenly distributed subgroups of ethnicity and body size could obscure trends and produce biased estimates favouring overrepresented groups. Thereby limiting the detection of potential interactions between variables. These limitations suggest that future research should expand sample sizes and ensure balanced representation across ethnicities, genders, and body sizes, enhancing the robustness and generalizability of findings and allowing more accurate subgroup comparisons.

Despite these limitations, developing a simple and innovative body fat index is crucial to address New Zealand's unique demographic needs. Advancements in mobile health technology, including smartwatches and mobile applications, offer promising tools for supporting a novel index like BDI. Digital health tools provide real-time monitoring of health metrics (Ozdalga et al., 2012; Wallace et al., 2012) and by incorporating body fat distribution measurements like WHR, a mobile application using BDI, could offer a more accurate continuing representation of health risks associated with excess fat, for example cardiovascular disease and metabolic syndrome. An accessible and user-friendly digital index could promote adoption and allow individuals to track their health status more accurately (Frankenfield et al., 2001; Gutin, 2018).

Considering New Zealand's high obesity rates and geographic barriers in rural areas, such a mobile application could be instrumental in overcoming healthcare access limitations. With obesity rates among the highest in the OECD (Utter et al., 2015), a mobile index based on BDI could be particularly valuable for underserved populations. It would empower both individuals and healthcare providers to access reliable health data, fostering more effective health interventions and reducing the stigma associated with BMI classification. This approach has the potential to improve overall health outcomes and address New Zealand's rising health disparities, especially in remote regions.

It is essential to recognize that both BMI and BDI, like any future index, serve as indicators of fat mass and do not provide a complete picture of individual health. As Gutin (2021) emphasizes, these measures are simply numbers and become valuable only when their clinical significance is understood and integrated into broader health assessments. Fat mass indices should be interpreted as part of a holistic health assessment, incorporating a multidimensional approach to health that encompasses physical, mental, spiritual, social, and environmental dimensions (Askheim et al., 2017). In line with the World Health Organization's definition of health as a state of physical, mental, and social well-being (WHO, 2020), a simple inclusive health measurement approach remains necessary to capture the complexities of individual health.

While BMI remains a widely recognized health measure, the development of a more inclusive, accurate, and personalized health index could significantly impact public health in New Zealand. Supported by both clinical experts and technological innovation, a simple index like BDI could challenge traditional BMI classifications, reducing the associated stigma, and enable a broader demographic to assess their health more accurately. By encouraging a shift toward comprehensive health measurement, BDI could ultimately foster better health outcomes and provide significant value both within New Zealand and on a global scale.

Chapter 6 Conclusion

Accurately quantifying fat mass has never been more critical, as the global obesity epidemic continues to escalate, posing serious health risks (Stein & Colditz, 2004). This research underscores the urgent need for a more refined and inclusive index than BMI to estimate fat mass effectively across diverse populations. A straightforward, stigma-free estimate of fat mass would empower individuals with a clearer understanding of their body composition, guiding them toward informed decisions about their health. The simple novel Bodyfat Distribution Index (BDI) introduced here offers a more accurate estimation of body fat percentage than BMI, successfully addressing some of BMI's fundamental limitations by better differentiating between men and women, and partially accounting for ethnic variations. This study demonstrates that BDI, built from simple anthropometric measures, improves fat percentage predictability by 15% compared to BMI, and that if digitised through an app, could provide widespread accessibility and lead to more effective, personalized health strategies and outcomes.

References

Arif, M., Gaur, D. K., Gemini, N., Iqbal, Z. A., & Alghadir, A. H. (2022). Correlation of percentage body fat, waist circumference and waist-to-hip ratio with abdominal muscle strength. Healthcare,

Ashwell, M., & Lejeune, S. (1996). Ratio of waist circumference to height may be better indicator of need for weight management. *Bmj, 312*(7027), 377.

Askheim, C., Sandset, T., & Engebretsen, E. (2017). Who cares? The lost legacy of Archie Cochrane. *Medical Humanities, 43*(1), 41-46.

Bjorntorp, P. (2002). Definition and classification of obesity. *Eating disorders and obesity: A comprehensive handbook, 2*, 377-381.

Blackburn, H., & Jacobs Jr, D. (2014). Commentary: Origins and evolution of body mass index (BMI): continuing saga. *International journal of epidemiology, 43*(3), 665-669.

Böhm, A., & Heitmann, B. (2013). The use of bioelectrical impedance analysis for body composition in epidemiological studies. *European journal of clinical nutrition, 67*(1), S79-S85.

Bray, G. A. (2014). *Handbook of Obesity--Volume 1: Epidemiology, Etiology, and Physiopathology* (Vol. 1). CRC Press.

Bray, G. A., & Popkin, B. M. (1998). Dietary fat intake does affect obesity! *The American journal of clinical nutrition, 68*(6), 1157-1173.

Browning, L. M., Hsieh, S. D., & Ashwell, M. (2010). A systematic review of waist-to-height ratio as a screening tool for the prediction of cardiovascular disease and diabetes: 0· 5 could be a suitable global boundary value. *Nutrition research reviews, 23*(2), 247-269.

Brug, J., Wammes, B., Kremers, S., Giskes, K., & Oenema, A. (2006). Underestimation and overestimation of personal weight status: associations with socio-demographic characteristics and weight maintenance intentions. *Journal of Human Nutrition and Dietetics, 19*(4), 253-262.

Burkhauser, R. V., & Cawley, J. (2008). Beyond BMI: the value of more accurate measures of fatness and obesity in social science research. *Journal of health economics, 27*(2), 519-529.

Burton, R. (2007). Why is the body mass index calculated as mass/height2, not as mass/height3? *Annals of human biology, 34*(6), 656-663.

Callahan, E. A., National Academies of Sciences, E., & Medicine. (2023). The Science, Strengths, and Limitations of Body Mass Index. Translating Knowledge of Foundational Drivers of Obesity into Practice: Proceedings of a Workshop Series, Carr, D., & Friedman, M. A. (2005). Is obesity stigmatizing? Body weight, perceived discrimination, and psychological well-being in the United States. *Journal of health and social behavior, 46*(3), 244-259.

Chooi, Y. C., Ding, C., & Magkos, F. (2019). The epidemiology of obesity. *Metabolism, 92*, 6-10.

Chugh, T. (2004). Bioelectrical impedance analysis. *University of Toronto Medical Journal, 81*(3), 243-245.

Chumlea, W. C., Guo, S. S., Kuczmarski, R. J., Flegal, K. M., Johnson, C. L., Heymsfield, S. B., Lukaski, H. C., Friedl, K., & Hubbard, V. S. (2002). Body composition estimates from NHANES III bioelectrical impedance data. *International journal of obesity, 26*(12), 1596-1609.

Culyer, A. J., & Newhouse, J. P. (2000). *Handbook of health economics*. Elsevier.

de Saint-Genoisstraat, (2021). J. Multidirectional regression analysis.

Deurenberg, P., & Deurenberg-Yap, M. (2003). Validity of body composition methods across ethnic population groups. *Acta diabetologica, 40*, s246-s249.

Deurenberg, P., Yap, M., & Van Staveren, W. A. (1998). Body mass index and percent body fat: a meta analysis among different ethnic groups. *International journal of obesity, 22*(12), 1164-1171.

Deurenberg-Yap, M., Schmidt, G., van Staveren, W. A., & Deurenberg, P. (2000). The paradox of low body mass index and high body fat percentage among Chinese, Malays and Indians in Singapore. *International journal of obesity, 24*(8), 1011-1017.

Dhurandhar, E. (2016). The downfalls of BMI-focused policies. *International journal of obesity, 40*(5), 729-730.

Ditmier, L. F. (2006). *New developments in obesity research*. Nova Publishers.

Duncan, J., Duncan, E. K., & Schofield, G. (2009). Accuracy of body mass index (BMI) thresholds for predicting excess body fat in girls from five ethnicities. *Asia Pacific journal of clinical nutrition, 18*(3), 404-411.

Etchison, W. C., Bloodgood, E. A., Minton, C. P., Thompson, N. J., Collins, M. A., Hunter, S. C., & Dai, H. (2011). Body mass index and percentage of body fat as indicators for obesity in an adolescent athletic population. *Sports health, 3*(3), 249-252.

Flegal, K. M., Kit, B. K., Orpana, H., & Graubard, B. I. (2013). Association of all-cause mortality with overweight and obesity using standard body mass index categories: a systematic review and meta-analysis. *Jama, 309*(1), 71-82.

Flegal, K. M., Shepherd, J. A., Looker, A. C., Graubard, B. I., Borrud, L. G., Ogden, C. L., Harris, T. B., Everhart, J. E., & Schenker, N. (2009). Comparisons of percentage body fat, body mass index, waist circumference, and waist-stature ratio in adults. *The American journal of clinical nutrition, 89*(2), 500-508.

Fletcher, I. (2014). Defining an epidemic: the body mass index in British and US obesity research 1960–2000. *Sociology of health & illness, 36*(3), 338-353.

Florey, C. d. V. (1970). The use and interpretation of ponderal index and other weight-height ratios in epidemiological studies. *Journal of chronic diseases, 23*(2), 93-103.

Forbes, G. B., & Forbes, G. B. (1987). Body composition in infancy, childhood, and adolescence. *Human Body Composition: Growth, Aging, Nutrition, and Activity*, 125-168.

Frank, A. P., de Souza Santos, R., Palmer, B. F., & Clegg, D. J. (2019). Determinants of body fat distribution in humans may provide insight about obesity-related health risks. *Journal of lipid research, 60*(10), 1710-1719.

Frankenfield, D. C., Rowe, W. A., Cooney, R. N., Smith, J. S., & Becker, D. (2001). Limits of body mass index to detect obesity and predict body composition. *Nutrition, 17*(1), 26-30.

Gallagher, D., Visser, M., Sepulveda, D., Pierson, R. N., Harris, T., & Heymsfield, S. B. (1996). How useful is body mass index for comparison of body fatness across age, sex, and ethnic groups? *American journal of epidemiology, 143*(3), 228-239.

Gardner, R. M. (2014). Weight status and the perception of body image in men. *Psychology research and behavior management*, 175-184.

González-Ruíz, K., Medrano, M., Correa-Bautista, J. E., García-Hermoso, A., Prieto-Benavides, D. H., Tordecilla-Sanders, A., Agostinis-Sobrinho, C., Correa-Rodríguez, M., Schmidt Rio-Valle, J., & González-Jiménez, E. (2018). Comparison of bioelectrical impedance analysis, slaughter skinfold-thickness equations, and dual-energy X-ray absorptiometry for estimating body fat percentage in Colombian children and adolescents with excess of adiposity. *Nutrients, 10*(8), 1086.

Gutin, I. (2018). In BMI we trust: reframing the body mass index as a measure of health. *Social theory & health: STH, 16*(3), 256.

Gutin, I. (2021). Body mass index is just a number: Conflating riskiness and unhealthiness in discourse on body size. *Sociology of health & illness, 43*(6), 1437-1453.

Ha, J., & Baek, K.-H. (2020). Body mass index at the crossroads of osteoporosis and type 2 diabetes. *The Korean Journal of Internal Medicine, 35*(6), 1333.

Hariri, A. F., Almatrafi, M. N., Zamka, A. B., Babaker, A. S., Fallatah, T. M., Althouwaibi, O. H., & Hamdi, A. S. (2019). Relationship between body mass index and T-scores of bone mineral density in the hip and spine regions among older adults with diabetes: a retrospective review. *Journal of obesity, 2019*(1), 9827403.

Heymsfield, S. B., Peterson, C. M., Thomas, D. M., Heo, M., & Schuna Jr, J. (2016). Why are there race/ethnic differences in adult body mass index–adiposity relationships? A quantitative critical review. *Obesity reviews, 17*(3), 262-275.

Houghton, P. (1990). The adaptive significance of Polynesian body form. *Annals of human biology, 17*(1), 19-32.

Hsieh, S., & Yoshinaga, H. (1995). Abdominal fat distribution and coronary heart disease risk factors in men-waist/height ratio as a simple and useful predictor. *International journal of obesity and related metabolic disorders: journal of the International Association for the Study of Obesity, 19*(8), 585-589.

Hsu, W. C., Boyko, E. J., Fujimoto, W. Y., Kanaya, A., Karmally, W., Karter, A., King, G. L., Look, M., Maskarinec, G., & Misra, R. (2012). Pathophysiologic differences among Asians, native Hawaiians, and other Pacific Islanders and treatment implications. *Diabetes care, 35*(5), 1189.

Jackson, A. S., Stanforth, P. R., Gagnon, J., Rankinen, T., Leon, A. S., Rao, D., Skinner, J. S., Bouchard, C., & Wilmore, J. H. (2002). The effect of sex, age and race on estimating percentage body fat from body mass index: The Heritage Family Study. *International journal of obesity, 26*(6), 789-796.

James, P. T., Leach, R., Kalamara, E., & Shayeghi, M. (2001). The worldwide obesity epidemic. *Obesity research, 9*(S11), 228S-233S.

James, P. T., Rigby, N., Leach, R., & Force, I. O. T. (2004). The obesity epidemic, metabolic syndrome and future prevention strategies. *European Journal of Cardiovascular Prevention & Rehabilitation, 11*(1), 3-8.

Jebb, S. A. (1999). Obesity: from molecules to man. *Proceedings of the Nutrition Society, 58*(1), 1-14.

Jutel, A. (2009). Sociology of diagnosis: a preliminary review. *Sociology of health & illness, 31*(2), 278-299.

Keller, K., Coldewey, M., & Engelhardt, M. (2014). Muscle mass and strength loss with aging. *Gazz. Med. Ital. Arch. Sci. Med, 173*, 477-483.

Keys, A., Fidanza, F., Karvonen, M. J., Kimura, N., & Taylor, H. L. (1972). Indices of relative weight and obesity. *Journal of chronic diseases, 25*(6-7), 329-343.

Keys, A., Fidanza, F., Karvonen, M. J., Kimura, N., & Taylor, H. L. (2014). Indices of relative weight and obesity. *International journal of epidemiology, 43*(3), 655-665.

Kok, P., Seidell, J. C., & Meinders, A. (2004). The value and limitations of the body mass index (BMI) in the assessment of the health risks of overweight and obesity. *Nederlands tijdschrift voor geneeskunde, 148*(48), 2379-2382.

Kolose, S., Hume, P. A., Stewart, T. I., Tomkinson, G. R., Stewart, A., & Legg, S. J. (2021). *Three-Dimensional Physique Assessment in the Military: New Zealand Defence Force Anthropometry Survey Protocols and Summary Statistics*. Auckland University of Technology, JE Lindsay Carter Kinanthropometry Clinic ….

Kontogianni, M. D., Panagiotakos, D. B., & Skopouli, F. N. (2005). Does body mass index reflect adequately the body fat content in perimenopausal women? *Maturitas, 51*(3), 307-313.

Kyle, U. G., Bosaeus, I., De Lorenzo, A. D., Deurenberg, P., Elia, M., Gómez, J. M., Heitmann, B. L., Kent-Smith, L., Melchior, J.-C., & Pirlich, M. (2004). Bioelectrical impedance analysis—part II: utilization in clinical practice. *Clinical nutrition, 23*(6), 1430-1453.

Lohman, T. G. (1989). Assessment of body composition in children. *Pediatric Exercise Science, 1*(1), 19-30.

Lourie, J. (1972). Hand-clasping and arm-folding among Middle Eastern Jews in Israel. *Human Biology*, 329-334.

Lukaski, H. C. (1996). Biological indexes considered in the derivation of the bioelectrical impedance analysis. *The American journal of clinical nutrition, 64*(3), 397S-404S.

Margaret Ashwell, Sigrid Gibson; Waist to Height Ratio Is a Simple and Effective Obesity Screening Tool for Cardiovascular Risk Factors: Analysis of Data from the British National Diet and Nutrition Survey of Adults Aged 19–64 Years. *Obes Facts* 1 April 2009; 2 (2): 97–103. https://doi.org/10.1159/000203363

Marfell-Jones, M., Nevill, A. M., & Stewart, A. D. (2012). Anthropometric surrogates for fatness and health. In *Body composition in sport, exercise and health* (pp. 126-146). Routledge.

Marfell-Jones, M., Olds, T., Stewart, A., & Carter, L. (2006). International standards for anthropometric assessment (2006).

McCarthy, H. D. (2006). Body fat measurements in children as predictors for the metabolic syndrome: focus on waist circumference. *Proceedings of the Nutrition Society, 65*(4), 385-392.

Lippincott williams & wilkins. Medicine, A. C. o. S. (2013a). *ACSM's guidelines for exercise testing and prescription*.

Meeuwsen, S., Horgan, G., & Elia, M. (2010). The relationship between BMI and percent body fat, measured by bioelectrical impedance, in a large adult sample is curvilinear and influenced by age and sex. *Clinical nutrition, 29*(5), 560-566.

Mei, Z., Grummer-Strawn, L. M., Pietrobelli, A., Goulding, A., Goran, M. I., & Dietz, W. H. (2002). Validity of body mass index compared with other body-composition screening indexes for the assessment of body fatness in children and adolescents. *The American journal of clinical nutrition, 75*(6), 978-985.

Mialich, M. S., Sicchieri, J. F., & Junior, A. J. (2014). Analysis of body composition: a critical review of the use of bioelectrical impedance analysis. *Int J Clin Nutr, 2*(1), 1-10.

Must, A., Dallal, G. E., & Dietz, W. H. (1991). Reference data for obesity: 85th and 95th percentiles of body mass index (wt/ht2) and triceps skinfold thickness. *The American journal of clinical nutrition, 53*(4), 839-846.

Nevill, A. M., Stewart, A. D., Olds, T., & Holder, R. (2006). Relationship between adiposity and body size reveals limitations of BMI. *American Journal of Physical Anthropology: The Official Publication of the American Association of Physical Anthropologists, 129*(1), 151-156.

Norton, K., & Eston, R. (2019). *Kinanthropometry and exercise physiology*. Routledge London, UK:.

Nuttall, F. Q. (2015). Body mass index: obesity, BMI, and health: a critical review. *Nutrition today, 50*(3), 117-128.

Stats NZ (2018). Ethnic group summaries reveal New Zealand's multicultural make-up. https://www.stats.govt.nz/news/ethnic-group-summaries-reveal-new-zealands-multicultural-make-up/

Ogden, C. L., Carroll, M. D., Curtin, L. R., McDowell, M. A., Tabak, C. J., & Flegal, K. M. (2006). Prevalence of overweight and obesity in the United States, 1999-2004. *Jama, 295*(13), 1549-1555.

World Health Organization, (1995). *Physical status: The use of and interpretation of anthropometry, Report of a WHO Expert Committee*.

World Health Organization, (2000). Obesity: preventing and managing the global epidemic: report of a WHO consultation.

World Health Organization, (2020). *Basic documents: (including amendments adopted up to 31 May 2019)*.

Ozdalga, E., Ozdalga, A., & Ahuja, N. (2012). The smartphone in medicine: a review of current and potential use among physicians and students. *Journal of medical Internet research, 14*(5), e1994.

Park, S.-H., Choi, S.-J., Lee, K.-S., & Park, H.-Y. (2009). Waist circumference and waist-to-height ratio as predictors of cardiovascular disease risk in Korean adults. *Circulation Journal, 73*(9), 1643-1650.

Peltz, G., Aguirre, M. T., Sanderson, M., & Fadden, M. K. (2010). The role of fat mass index in determining obesity. *American Journal of Human Biology, 22*(5), 639-647.

Peterson, C. M., Su, H., Thomas, D. M., Heo, M., Golnabi, A. H., Pietrobelli, A., & Heymsfield, S. B. (2017). Tri-ponderal mass index vs body mass index in estimating body fat during adolescence. *JAMA pediatrics, 171*(7), 629-636.

Pi-Sunyer, F. X. (2002). Medical complications of obesity in adults. *Eating disorders and obesity: A comprehensive handbook, 2*, 467-472.

Pischon, T., Boeing, H., Hoffmann, K., Bergmann, M., Schulze, M. B., Overvad, K., Van Der Schouw, Y., Spencer, E., Moons, K., & Tjønneland, A. (2008). General and abdominal adiposity and risk of death in Europe. *New England Journal of Medicine, 359*(20), 2105-2120.

Prentice, A. M., & Jebb, S. A. (2001). Beyond body mass index. *Obesity reviews, 2*(3), 141-147.

Puhl, R. M., & Heuer, C. A. (2009). The stigma of obesity: a review and update. *Obesity, 17*(5), 941.

Quetelet, A. (1842). *A treatise on man and the development of his faculties*. W. and R. Chambers.

Radetti, G., Fanolla, A., Grugni, G., Lupi, F., Tamini, S., Cicolini, S., & Sartorio, A. (2021). The role of different indexes of adiposity and body composition for the identification of metabolic syndrome in women with obesity. *Journal of Clinical Medicine, 10*(9), 1975.

Ræder, H., Kværner, A. S., Henriksen, C., Florholmen, G., Henriksen, H. B., Bøhn, S. K., Paur, I., Smeland, S., & Blomhoff, R. (2018). Validity of bioelectrical impedance analysis in estimation of fat-free mass in colorectal cancer patients. *Clinical nutrition, 37*(1), 292-300.

Ranasinghe, C., Gamage, P., Katulanda, P., Andraweera, N., Thilakarathne, S., & Tharanga, P. (2013). Relationship between body mass index (BMI) and body fat percentage, estimated by bioelectrical impedance, in a group of Sri Lankan adults: a cross sectional study. *BMC Public Health, 13*, 1-8.

Rich, E., & Evans, J. (2005). 'Fat ethics'–The obesity discourse and body politics. *Social Theory & Health, 3*, 341-358.

Robinson, E., & Oldham, M. (2016). Weight status misperceptions among UK adults: the use of self-reported vs. measured BMI. *BMC obesity, 3*, 1-6.

Roehling, M. V., Roehling, P. V., & Pichler, S. (2007). The relationship between body weight and perceived weight-related employment discrimination: The role of sex and race. *Journal of Vocational Behavior, 71*(2), 300-318.

Rush, E. C., Freitas, I., & Plank, L. D. (2009). Body size, body composition and fat distribution: comparative analysis of European, Maori, Pacific Island and Asian Indian adults. *British Journal of Nutrition, 102*(4), 632-641.

Saguy, A. C., & Almeling, R. (2008). Fat in the fire? science, the news media, and the “obesity epidemic” 2. Sociological Forum,

Shiely, F., & Millar, S. R. (2021). BMI self-selection: Exploring alternatives to self-reported BMI. *Research Methods in Medicine & Health Sciences, 2*(3), 112-122.

Sims, E. A. (2001). Are there persons who are obese, but metabolically healthy? *Metabolism-Clinical and Experimental, 50*(12), 1499-1504.

Sluyter, J. D., Schaaf, D., Scragg, R. K., & Plank, L. D. (2011). Body mass index and percent body fat in a New Zealand multi-ethnic adolescent population. *International Journal of Pediatric Obesity, 6*(1), 36-44.

Smalley, K. J., Knerr, A. N., Kendrick, Z. V., Colliver, J. A., & Owen, O. E. (1990). Reassessment of body mass indices. *The American journal of clinical nutrition, 52*(3), 405-408.

Spahlholz, J., Baer, N., König, H. H., Riedel-Heller, S. G., & Luck-Sikorski, C. (2016). Obesity and discrimination–a systematic review and meta-analysis of observational studies. *Obesity reviews, 17*(1), 43-55.

Stein, C. J., & Colditz, G. A. (2004). The epidemic of obesity. *The Journal of Clinical Endocrinology & Metabolism, 89*(6), 2522-2525.

Stini, W. A. (1975). Adaptive strategies of human populations under nutritional stress. *Biosocial interrelations in population adaptation*, 19-41.

Sun, G., French, C. R., Martin, G. R., Younghusband, B., Green, R. C., Xie, Y.-g., Mathews, M., Barron, J. R., Fitzpatrick, D. G., & Gulliver, W. (2005). Comparison of multifrequency bioelectrical impedance analysis with dual-energy X-ray absorptiometry for assessment of percentage body fat in a large, healthy population. *The American journal of clinical nutrition, 81*(1), 74-78.

Swainson, M. G., Batterham, A. M., Tsakirides, C., Rutherford, Z. H., & Hind, K. (2017). Prediction of whole-body fat percentage and visceral adipose tissue mass from five anthropometric variables. *PloS one, 12*(5), e0177175.

Tan, K. (2004). Appropriate body-mass index for Asian populations and its implications for policy and intervention strategies. *The Lancet*.

Thomson, R., Brinkworth, G. D., Buckley, J. D., Noakes, M., & Clifton, P. M. (2007). Good agreement between bioelectrical impedance and dual-energy X-ray absorptiometry for estimating changes in body composition during weight loss in overweight young women. *Clinical nutrition, 26*(6), 771-777.

Tomiyama, A. J., Carr, D., Granberg, E. M., Major, B., Robinson, E., Sutin, A. R., & Brewis, A. (2018). How and why weight stigma drives the obesity 'epidemic'and harms health. *BMC medicine, 16*, 1-6.

Tomiyama, A. J., Hunger, J. M., Nguyen-Cuu, J., & Wells, C. (2016). Misclassification of cardiometabolic health when using body mass index categories in NHANES 2005–2012. *International journal of obesity, 40*(5), 883-886.

Trefethen, N. (2013, 29 August 2013). *Calculate Your 'New BMI*. URL: http://people.maths.ox.ac.uk/trefethen/bmi. html (accessed 29 August 2013).

Utter, J., Denny, S., Teevale, T., Peiris-John, R., & Dyson, B. (2015). Prevalence and recent trends in overweight, obesity, and severe obesity among New Zealand adolescents. *Childhood obesity, 11*(5), 585-589.

Van Haute, M., Rondilla, E., Vitug, J. L., Batin, K. D., Abrugar, R. E., Quitoriano, F., Dela Merced, K., Maaño, T., Higa, J., & Almoro, J. G. (2020). Assessment of a proposed BMI formula in predicting body fat percentage among Filipino young adults. *Scientific Reports, 10*(1), 21988.

Visaria, A., & Setoguchi, S. (2023). Body mass index and all-cause mortality in a 21st century US population: A National Health Interview Survey analysis. *PloS one, 18*(7), e0287218.

Wagner, D. R., & Heyward, V. H. (2000). Measures of body composition in blacks and whites: a comparative review. *The American journal of clinical nutrition, 71*(6), 1392-1402.

Wallace, S., Clark, M., & White, J. (2012). 'It's on my iPhone': attitudes to the use of mobile computing devices in medical education, a mixed-methods study. *BMJ open, 2*(4), e001099.

Walls, H. L., Backholer, K., Proietto, J., & McNeil, J. J. (2012). Obesity and trends in life expectancy. *Journal of obesity, 2012*(1), 107989.

Wellens, R. I., Roche, A. F., Khamis, H. J., Jackson, A. S., Pollock, M. L., & Siervogel, R. M. (1996). Relationships between the body mass index and body composition. *Obesity research, 4*(1), 35-44.

Yoo, E.-G. (2016). Waist-to-height ratio as a screening tool for obesity and cardiometabolic risk. *Korean journal of pediatrics, 59*(11), 425.

Yusuf, S., Hawken, S., Ôunpuu, S., Bautista, L., Franzosi, M. G., Commerford, P., Lang, C. C., Rumboldt, Z., Onen, C. L., & Lisheng, L. (2005). Obesity and the risk of myocardial infarction in 27 000 participants from 52 countries: a case-control study. *The Lancet, 366*(9497), 1640-1649.