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Utilizing Anthropometric Measurements and 3D Scanning for Health Assessment in Clinical Practice

REVIEW

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MEIZI WANG
YANG SONG
XIANGLIN ZHAO
YAN WANG
MING ZHANG

*Author affiliations can be found in the back matter of this article

ABSTRACT

Anthropometric measurement as a traditional method for estimating human body dimension has been widely used among diverse scientific disciplines. In the clinical setting, anthropometric data could be used to assess body composition and nutrition status, predict obesity-related health risks, and respond to treatments. Nowadays, the development of 3D scanning technology and in-depth data analysis has innovated the way of anthropometric measurement and its application. This study provides an overview of the current application of anthropometric measurement in clinical practice, we first describe the application of anthropometric indicators in the health assessment, and highlight its advantages and limitations. We then outline 3D scanning technology for anthropometric measurement and explore its potential applications from various perspectives. Overall, regarding the application of anthropometric measurements in health assessment, it is essential to establish assessment criteria targeted to specific population groups, considering the diversity in anthropometric characteristics among various ages, genders, ethnicities, and demographics. Furthermore, with the development of statistical modelling techniques, the extensive anthropometric data collected by 3D scanning can achieve its maximum benefit in the field of biological health.

CORRESPONDING AUTHOR:

Ming Zhang

Department of Biomedical Engineering, The Hong Kong Polytechnic University, Hong Kong 999077, China; Research Institute for Sports Science and Technology, The Hong Kong Polytechnic University, Hong Kong 999077, China

ming.zhang@polyu.edu.hk

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INTRODUCTION

Anthropometric measurement stands as one of the most portable, universally applicable, and non-invasive method to assess variation and change in the form of human body, including aspects like proportion, size, shape, and composition. Through the end of 19th century, in response to the demands of early modern military recruitment, anthropometric measurement emerged as a new tool gained importance in screening and monitoring of adequate growth individual and populations (De Onis and Habicht, 1996). Towards the modern society, there has been a significant global surge in anthropometric surveys through the diverse age and ethnic demographics. Such anthropometric information plays a fundamental role across multiple domains (Figure 1), involving apparel and fashion industry, ergonomics design, human factors, etc. (Heymsfield et al., 2018). Furthermore, those data are of great interest to dietitians-nutritionists, sports specialists, and healthcare practitioners (Kennedy et al., 2022).

In clinical settings, anthropometric indices are the most widely used tool served as an essential indicator to diagnose obesity or thinness, monitor therapeutic intervention, and measure physical fitness progress on health or nutritional status (Rumbo-Rodríguez et al., 2021). The World Health Organization (WHO) has provided guidelines for the appropriate interpretation and utilization of anthropometric indices in the public health and clinical decision-making (Easterby et al., 2012). Notably, anthropometric indices such as body mass index (BMI), waist circumference (WC), and waist-to-hip ratio (WHR), which are derived from the core anthropometric components (height, weight, circumference), have found an extensive application in the obesity assessment and metabolic disorder identification (Ashwell et al., 2012; Carmienke et al., 2013; Correa et al., 2016). The work of Sommer et al. highlighted the efficacy of anthropometric tool in obesity assessment after demonstrating a systemic review based on the 32 studies (Sommer et al., 2020). Also, Jayedi et al. identified 26 million individuals from 216 cohort studies, underscoring a relationship between the key anthropometric indicators (BMI and WC) and the risk of developing type 2 diabetes (Jayedi et al., 2022). In addition, more accuracy of anthropometric indicators could be developed, as the numerous anthropometric measurements can be directly and efficiently obtained through 3D scanning.

The application of 3D scanning technology has innovated the way of anthropometric data collection. Comparing to the traditional manual methods using calipers and measuring tape, 3D scanning offers remarkable efficiency and reproducibility, providing highly detailed, and accurate measurement (Bogo et al., 2014; Haleem and Javaid, 2019). Several prevalent 3D scanning technologies are commonly used for anthropometric measurement, including passive stereo (PS), structured light (SL), and time-of-light imaging (ToF). The reliability and agreement of anthropometric measurements derived from 3D scans have been thoroughly validated (Ladouceur et al., 2017; Medina-Inojosa et al., 2016; Ng et al., 2016). A systematic review including 18 studies, which evaluated various scanning technologies, demonstrated a robust correlation between 3D and reference measurements (Rumbo-Rodríguez et al., 2021). Due to the varying degrees of success and acceptance that 3D scanning technology has received, it has become possible to conduct large-scale anthropometric surveys. Under this context, the nationwide anthropometric dataset across diverse age groups and ethnicities has been established among the various countries.

In recent years, considerable development has taken place in the surveying and collection of anthropometric data. The utilization of such data by clinicians, engineers, and industrial designers has experienced a substantial increase. In particular, 3D scanning technology has brought new opportunities for enhancing body composition assessment by integrating advanced statistical techniques. Accordingly, the primary objective of this study is two-fold: first, to offer a comprehensive overview of applications of anthropometric measurements in health risk assessment; second, to critically examine the utility of 3D scanning technology in clinical settings and explore its potential for future applications. For this purpose, original publications focusing on anthropometric measurement were searched in PubMed, MEDLINE, Web of Science, and Scopus. The search terms used were: “anthropometric survey”, “anthropometric indicator”, “indices”, “3D scanning”, “anthropometric data”, “health and nutrition status”, alone and in combination.

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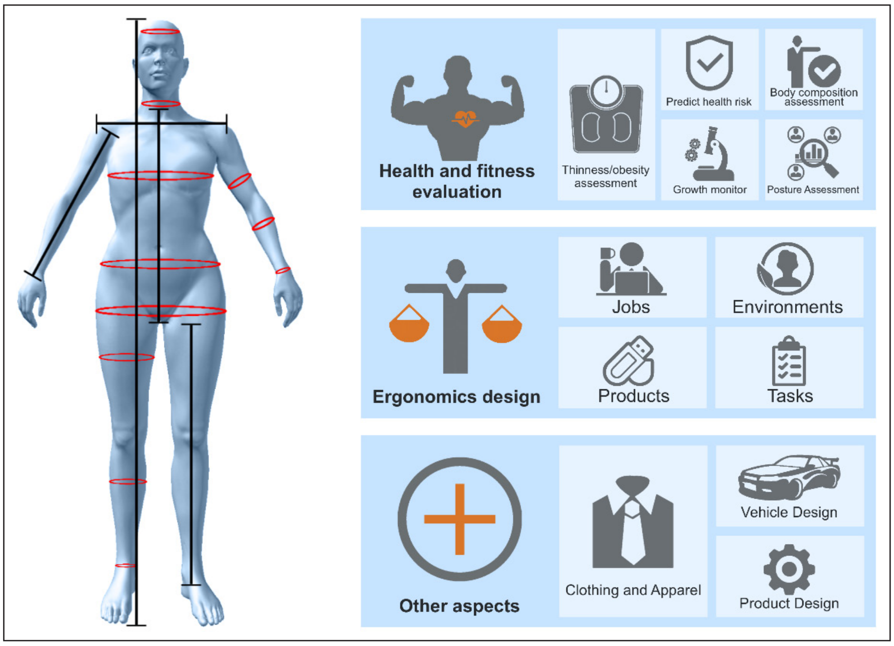

Figure 1 The diverse applications of anthropometric measurements.

THE APPLICATION OF ANTHROPOMETRIC MEASUREMENT IN CLINICAL PRACTICE

Anthropometric indicator represents mathematical relationships by calculating ratios, proportions, or other potential relationship based on specific body measurement, such as height, weight, circumferences, length, and skinfold thickness (Arroyo et al., 2014; Ehrampoush et al., 2017). Anthropometric indicators could serve purposes like identifying health risks, assessing fitness, and guiding treatment interventions. Piqueras et al.'s work, for instance, identified 17 anthropometric health indicators relevant to obesity assessment (Ehrampoush et al., 2017). However, despite their potential, only a limited number of anthropometric indicators have gained widespread acceptance in clinical settings. To provide clarity, we have compiled a list of commonly used indicators from existing literature.

Moreover, in this section, the attention to the application of anthropometric indices has been primarily centered on the Chinese population. Recognizing the considerable diversity in anthropometric characteristics among various ethnic groups, it is evident that a one-size-fits-all approach is not suitable. Consequently, it holds practical significance to concentrate on a specific demographic. So far, there is no comprehensive description of application of anthropometric indices in Chinese population, despite the considerable challenges posed by the issues of obesity and metabolic disorders in current Chinese society. Hence, it is imperative to underscore the application of anthropometric indices and their existing limitations in the Chinese population

BODY MASS INDEX

Body mass index (BMI) is one of the widely used indices, which relates to body mass (kg) and height (m):

$$\mathrm{BMI}\,(\mathrm{kg/m^2}) = \frac{\mathrm{weight\,(kg)}}{\mathrm{height\,(m)}^2}$$

It provides an approximate indicator of body fatness for assessing obesity status in the general population (Aune et al., 2016). Different cutoffs of BMI have been used to classify individuals among various age groups, gender, and ethnicities. For the Asian population, the BMI is generally lower compared to those used for other ethnic groups. In Asian adults, BMI is considered normal when BMI ranging from 18.5 to 23 kg/m^2, and obesity when BMI is over 27.5 kg/m^2. In Western adults, the normal BMI range is from 18.5 to 24.9 kg/m^2, and obesity with BMI is over 30 kg/m^2 (Tan 2004; Wildman et al., 2004). However, BMI has its deficiencies as it does not account for factors like body composition, including visceral fat and fat distribution (Ashwell et al., 2012; Böhm and Heitmann, 2013). Additionally, Sarria et al. have suggested that BMI may not be sensitive enough to estimate obese children and adolescents, and more measurement methods such as waist circumference, skinfold thickness, and bioelectrical impedance were required instead (Sarria et al., 2001).

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WAIST CIRCUMFERENCE

Waist Circumference (WC) has showed well-correlated with the body fat percentage, it is commonly used to assess the body fat in the adult populations (Heo et al., 2013). It can be directly measured at the waist; however, the definition of waist level has not yet met the consensus (Ross et al., 2008). WHO recommends a widely used measurement protocol in which the waist level is situated at the approximate midpoint between the lower margin of the last palpable rib and the top of the iliac crest (Ostchega et al., 2021). The cutoff point of WC recommended for Asians are 90 cm and 80 cm for male and female respectively (Li et al., 2002; Lin et al., 2002; Tan et al., 2004). Clinically, WC is considered as one of the major indictors of assessing metabolic syndrome (Cerhan et al., 2014; Song et al., 2015; Zhang et al., 2008). A longitudinal study followed 10,419 Chinese adults with age ranging from 20–80 years old for hour years, revealed a stronger association between WC variability and the risk of type 2 diabetes when compared to BMI (Fan et al., 2020). Even though the WC could reflect the abdominal adiposity, it is still unable to distinguish between visceral and subcutaneous fat (Guan et al., 2016). Also, WC may lead to overestimation or underestimation of the obesity status of tall or short individuals since it does not take into account height differences.

WAIST-TO-HEIGHT RATIO (WHtR)

WHtR is calculated as the quotient between the height and WC:

$$\mathrm{WHtR} = \frac{\mathrm{WC\ (cm)}}{\mathrm{height\ (cm)}}$$

In recent years, it has been suggested that WHtR could present a higher diagnostic value than other anthropometric indicators for evaluating the central obesity (Ashwell et al., 2012; Eslami et al., 2023; Han et al., 2017; Wang et al., 2018). Particularly in children and adolescents, WHtR shows more sensitivity than other indicators, due to it changes slightly with age and gender and does not need of age and gender-specific charts for interpretation (Choi et al., 2017). The suggested cutoff point of WHtR as a marker for central obesity is 0.5 for both children and adults (Song et al., 2015; Wang et al., 2018; Schneider et al., 2010). But, the thresholds of WHtR are different among the various age periods and ethnicities (Dou et al., 2020; Matsha et al., 2013; Nambiar et al., 2010). Dong et al. investigated 13,379 Han adults aged from 18 to 95 years old covering 40 different institutions to determine the cutoff points of WHtR for metabolic syndrome in the Chinese population (Dong et al., 2019). They suggested the optimal cutoff point of 0.51 for males and 0.49 for females. The cutoff point in the different research is inconsistent, those values fluctuate around 0.5 (Lin et al., 2002; Cai et al., 2013; Dong et al., 2011; Ho et al., 2003; Silva et al., 2013). However, the cutoff point of WHtR among the demographic characteristics, age, height, and waist circumference has not been closely investigated in Chinese children and adolescents.

WAIST-TO-HIP RATIO (WHR)

WHR is calculated as the ratio between WC and hip circumference (HC):

$$\mathrm{WHR} = \frac{\mathrm{WC\ (cm)}}{\mathrm{HC\ (cm)}}$$

It has been regarded as a more precise indicator for visceral fat due to its emphasis on the effect of subcutaneous fat by involving HC (Cameron et al., 2013; Cameron et al., 2012). HC is measured at the level of the greatest posterior (back) protuberance of the buttocks, can be located at the iliac crests on both side of hip (World Health Organization 2011). WHO has recommended the WHR cutoff point of 1 for males and 0.8 for females, which is used to evaluate central obesity, and a higher WHR is related to an increased risk of metabolic disease (Motamed et al., 2015; World Health Organization 1997). Considering the various ages, genders, and ethnicities, the cutoff point of WHR is not always consistent with value fluctuating around 0.9 (Cao et al., 2018). The WHR has been proposed as a means to distinguish between 'pear-shaped' and 'apple-shaped' body types (Bener et al., 2013), gaining popularity through various media in more recent years. It is important to note that this classification method has not been widely accepted or utilized in the scientific medical field. Further in-depth research is necessary to determine whether it has potential value for health applications.

BODY FAT PERCENTAGE (BF%)

BF% is defined as the proportion of fat mass relative to the total body fat mass and is considered a core component of body composition (Qian et al., 2019). The wide diversity of anthropometric equations can be used to estimate the BF% (Freedman et al., 2013; Wohlfahrt et al., 2014). The equation of Siri and BroŽek equations based on the density of the human body have been widely used for adults (Brožek et al., 1963; Siri 1956). Siri and BroŽek's equations are given as:

$$\mathrm{BF\%}\,(\mathrm{Siri}) = \left(\frac{4.95}{\text{Body density}\,(\mathrm{kg/m^3})} - 4.50\right)100$$

$$\mathrm{BF\%}\,(\mathrm{Bro\check{Z}ek}) = \left(\frac{4.570}{\text{Body density}\,(\mathrm{kg/m^3})} - 4.142\right)100$$

Siri and BroŽek's equations are based on the assumption of a constant density of the body mass which the fat density is relatively consistent among individuals across ages. But, the density of fat free mass varies substantially in populations with different characteristics, such as age, gender, and ethnicity (Chumlea et al., 1992). Considering the gender difference, Liu et al. established sex-specific equation based on age, BMI, and WC to predict BF% among Chinese adults with age ranging from 50 to 70 years old, this predicted equation has been validated in large sample population and dual-energy X-ray absorptiometry (DXA), the equation is following (Liu et al., 2015):

$$\begin{aligned}\mathrm{BF\%} = {} & 44.65021389 + 0.43756706 \cdot \mathrm{BMI} + 0.96844999 \cdot \mathrm{WC} + 0.06394571 \cdot \mathrm{Age} + \\ & 19.21114033 \cdot \mathrm{Sex} - 0.00406036 \cdot \mathrm{WC}^2 - 0.08813980 \cdot \mathrm{Sex} \cdot \mathrm{WC} \\ & (\mathrm{Sex} = 0 \text{ for men, } 1 \text{ for women})\end{aligned}$$

Also, Henry et al. developed a new equation to predict BF% in Asian-Chinese Adults by using age, height, WC, and skinfold thickness, detailed information about the equation can be found in their work (Henry et al., 2018). However, it is important to acknowledge the common limitations in these studies. Such as, they exclusively focused on the participants from a single region, with a small sample size, had a limited age range. Further research is necessary to confirm the applicability of those equations in nationwide use. Moreover, it is worth noting that there is no consensus regarding the appropriate prediction equation for BF% (Lin et al., 2018; Sinaga et al., 2021). Cui et al. had identified 26 predicted equations of BF% in American adults, derived from previously published anthropometric equations (Cui et al., 2014). They concluded that the equation incorporating with WC exhibited optimal performance in men, while those involving BMI have adequately results in females, but equation containing skinfold thickness performed less well in older adults (Cui et al., 2014).

In terms of the cutoff point of BF%, WHO had proposed 25% for males and 35% for females in adult Caucasians (Ferreira 2020), but BF% varies among different population groups. Jia et al. indicated the cutoff point for predicting the risk of cardiometabolic abnormalities in the Chinese adult group was 24% for males and 33% for females, the data was based on the 2007–2008 China National Diabetes and Metabolic Disorders Study with 23,769 participants aged from 20–75 years old (Jia et al., 2018). Additionally, the vast majority BF% index is developed based on adult population and it needs to be modified for Children and adolescent.

FAT MASS INDEX (FMI) AND FAT FREE MASS INDEX (FFMI)

FMI and FFMI was first proposed in 1990, reflect the body weight status based on the change of fat mass or fat free mass or both (Schutz et al., 2002). Previous research demonstrated that increased FMI shows a positive relationship with the risk of metabolic syndrome (Kyle et al., 2005), and decreased FFMI has been suggested to be associated with increased mortality in elderly population (Genton et al., 2013; Graf et al., 2015; Han et al., 2010). The reference value of FMI and FFMI has been established worldwide as well as in China (Bahadori et al.,2006; Franssen et al., 2014; Jin et al., 2019; Kudsk et al., 2017). In 2018, Jin and colleagues presented reference values for FMI and FFMI specific to the Chinese population. Their study involved 9859 healthy adults from various ethnic backgrounds, ranging in age from 18 to 80 years, and revealed sex, age, and ethnic-specific distributions for FMI and FFMI (Jin et al., 2019). In this study the equation of FMI and FFMI is following:

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$$\mathrm{FFMI}\,(\mathrm{kg}/\mathrm{m}^2) = \frac{\text{Fat free mass (kg)}}{\text{Height (m)}^2}$$

$$\mathrm{FMI}\,(\mathrm{kg}/\mathrm{m}^2) = \frac{\text{Fat mass (kg)}}{\text{Height (m)}^2}$$

The fat mass and fat free mass can be obtained using bioelectrical impedance analysis. Lee et al. developed the practical anthropometric prediction equations for fat mass using anthropometric measurements including age, height, weight, waist, arm, calf, thigh, and triceps (lee et al., 2017). However, the study sample is limited to the American population restricted the applicability of the proposed equations to other ethnicities.

LEAN BODY MASS (LMS)

LBM has been considered a prominent predictor of body functions, playing an important role in various physiological processes, including metabolism, physical performance, and disease resistance (Li et al., 2019). It is even more important in the elderly population, as the aging process is associated with a significant reduction in LBM (Lee et al., 2017). Li et al., established sex-specific prediction equation of LMS for the health southern Chinese population in 2019 for the first time, the study included 12,194 subjects with age ranging from 18- to 97.9-year-old based on anthropometric data of height, weight, and BMI, and the equation as following (Li et al., 2019):

$$\text{For male group: } \mathrm{LBM\,(kg)} = -25.498 - 0.051 \cdot \mathrm{Age} + 0.312 \cdot \mathrm{Height} + 0.263 \cdot \mathrm{Weight} + 0.373 \cdot \mathrm{BMI}$$

$$\text{For female group: } \mathrm{LBM\,(kg)} = 8.032 + 0.534 \cdot \mathrm{Weight} + 0.070 \cdot \mathrm{Height} - 0.533 \cdot \mathrm{BMI}$$

The performance of this equation has been validated with DXA showing high predictability. However, this equation using simplest anthropometric data, using other measurements such as WC or hip circumference may enhance the accuracy of prediction equation of LBM. Furthermore, to ensure the applicability on a national scale, further investigation is required, as the study's subjects were limited to the southern region of China.

ANTHROPOMETRIC MEASUREMENT IN CHILDREN AND ADOLESCENTS

The WHO introduced updated standards in 2016 for estimating the growth and health status of children from birth to 5 years of age using serial of anthropometric measurements, including height, weight, skinfold, and head circumference (Pérez-Bermejo et al., 2021). These measurements provide valuable insights into a child's physical development and nutritional well-being. There are four primary anthropometric indicators to assess growth in children and adolescents: weight-for-age, height-for-age, weight-for-height, and BMI-for-age. Each of these indicators serves a distinct purpose in assessing various dimensions of well-being in children and adolescents, be able to identifying at-risk subject, implementing timely interventions, and monitoring progress to ensure healthy development. In addition, there is an increasingly recognized health problem in children and adolescents due to the rapid growth that occurs during childhood and adolescence, leading to significant changes in anthropometric characteristics (De Onis et al., 2006). As a result, it is recommended to include regular anthropometric measurements as part of routine health check-ups to monitor health status of children and adolescents. The Bright Futures/American Academy of Pediatrics (APP) established a set of 'periodicity schedules' to guide screening and assessments for child visits from infancy through adolescence (Workgroup et al., 2019).

Although, the WHO had already established and updated a comprehensive growth reference for children and adolescents based on those indicators, different countries or/regions should establish the specific one due to the inherent differences among the various ethnicities and geographical. For instance, the national survey on the physical growth of health children under 7 years old in nine Chinese cities which was conducted in 2015, the survey indicated that the physical growth of children under 7 years in 9 Chinese cities was taller and heavier than WHO standards (Zhang et al., 2017). Also, it was indicated that a slight difference was found in anthropometric measurements between urban and suburban children.

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ANTHROPOMETRIC MEASUREMENT IN ELDERLY

The number and proportion of old people growing fast worldwide, raising important medical and social problems (Rudnicka et al., 2020). In China, the percentage of elderly people had grown to 12.5% by the year 2010 and will continue growing to 30% in 2050 according to predictions (Lobanov-Rostovsky et al., 2023). Compared to other age groups, aging-related anthropometrical changes in the Chinese population have received limited attention so far. Considering the age aging process, a significant change could happen on both physiological and nutritional status which is highlighted by height decrease, weight decline, muscle mass loss, and body fat redistribution (Corish and Kennedy 2003; Pennathur and Dowling 2003; Perissinotto 2002). The current anthropometric standards, originally designed for younger age groups, may not be directly applicable to older individuals. This is because age-related factors like osteoporosis, muscle loss, postural changes, and kyphoscoliosis contribute to a gradual decline in both weight and height among the elderly. Consequently, these changes can reduce the reliability of the standard BMI classification system when applied to older people.

In addition, in the majority of contemporary studies on age-related anthropometric measurements, the primary focus is on examining the connection between BMI and body fat levels. Other anthropometric data, such as mid-arm circumference and calf circumference are important indicators to reflect body fatness and physical functional ability in the elderly (Tsai 2012). The severe decline in calf circumference is closely associated with aging-related functional decline and aging-related mobility impairment, whereas a significant decrease in mid-arm circumference usually happens on the final stage of mobility dysfunction (Mason et al., 2008). According to WHO's baseline report emphasizing the intrinsic capacity, functional ability and environmental factors are the major components for healthy aging (Michel et al., 2021). In 2007, Hu et al. collected anthropometric data and functional strength among 100 elderly Chinese females and males aged range 65.0–80.7, involving 47 anthropometric measurements and three functional strength measurements (handgrip strength, back strength, leg strength) (Hu et al., 2007). However, this survey was limited by a small sample size and a single region group in Beijing. Recently, the second collection of anthropometric data for adult Chinese conducted by the China National Institute of Standardization (CNIS) from 2014 to 2018 with a population age range from 18 to 75 years old, which presented a comprehensive update compared to the first national anthropometric survey with age range from 18 to 60 years in 1988 (Wang et al., 2018). By considering data from a wide age spectrum, researchers and policymakers can make more informed decisions and interventions to promote healthy aging among the elderly in China.

NOVEL ANTHROPOMETRY BASED ON 3D SCANNING

Comparing with traditional anthropometric measurement, 3D scanning offers a non-invasive and contactless approach, facilitating rapid data collection while ensuring accuracy and repeatability in measurements (Javaid and Haleem 2018; Volonghi et al., 2018). The utilization of 3D scanning for collecting anthropometric data began in 1989 with the pioneering work of Jones and West (Lu and Wang 2008). Over the subsequent three decades, remarkable progress has been achieved in methodologies aimed at quantifying human body shape, these advancements include diverse technologies, such as laser and structured light systems, millimeter wave radar, and multi-view camera methods (Kennedy et al., 2022). In recent years, numerous international/national/public organizations have using 3D whole-body scanners to gather anthropometric data and establish a database of human body model. For instance, the adult sizing surveys in UK and USA in 2004 using 3D body scanner to measure 22,000 subjects, the scanners automatically extracted 130 body measurements, which yielded statistical analysis report for each measurement involving mean, maximum/minimum, and frequency (Treleaven and Wells 2007). Also, 3D scanner has been used in a recent Chinese nationwide anthropometric survey conducted in 2014 covered six different regions with 32 cities, involving more than 26,000 individuals age 18 to 75 years old, resulting in a total of 169 measurements (Bartol et al., 2021) (Figure 2).

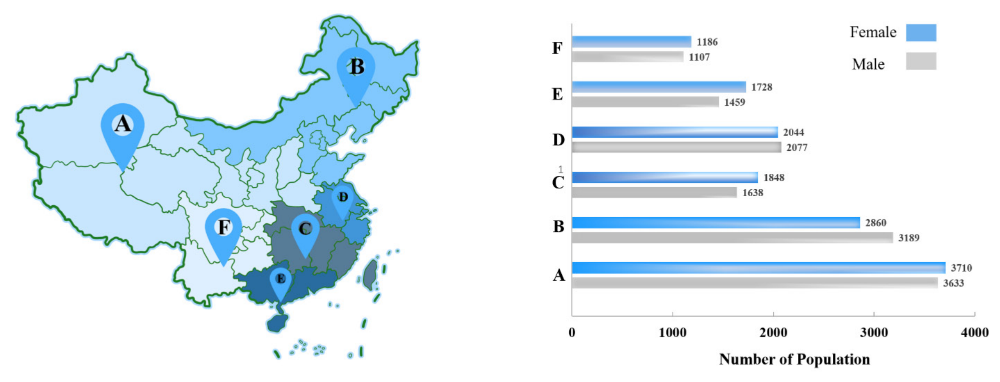

Figure 2 Population distribution of China national adult anthropometric survey, total population is 26,000.

3D SCANNING TECHNOLOGY

Various commercially available scanning systems utilize multiple techniques for 3D static scanning, with passive stereo, structured light (SL), photogrammetry, and time-of-flight imaging (ToF) being the primary methods. Among these, SL has been proposed to offer superior accuracy and resolution compared to the others, making it the preferred choice for quasi-static scanning (https://www.cnis.ac.cn/ [accessed 12.07.2023]). These scanning systems consist of different numbers of cameras and may incorporate static or dynamic components like rotating platforms. Subjects are instructed to assume specific predetermined poses and maintain stillness until the scanning process concludes within a matter of seconds. The scanning system usually generates 3D point cloud, depth maps, or set of RGB images. Different 3D scanner has their own specialized body measurement software, despite the specific variations in measurements, the fundamental principles of anthropometry remain consistent. These principles involve utilizing techniques like convex hulls or similar operations to compute body circumferences and contour lengths, identifying key joints and limbs as landmarks to define different body regions, and subsequently segmenting the body point cloud or mesh along various planes (Kennedy et al., 2022). With potential application of 3D scanning in large simple size survey and in clinical settings, the validation of 3D scanner in anthropometric measurements is important to demonstrate accuracy. The validation methods including flexible tape, DXA, Air displacement plethysmography (ADP), and electrical bioimpedance are commonly used to validate body composition and shape which is measured by 3D scanner (Bretschneider et al. 2009).

On the other hand, body movement is mostly captured with Motion Capture Technology, where landmarks are attached to the body, and the output displays an abstract skeleton for biomechanical analysis (Loper et al., 2014; Malleson et al., 2017; https://3dmd.com/products/ [accessed 12.07.2023]). However, this approach cannot capture the detail of soft-tissue deformation. Therefore, dynamic anthropometry has become an important research topic in recent years. Understanding how the human body undergoes changes during dynamic movements is crucial for studying the muscular system and the interplay between agonist and antagonist muscles. The technological evolution from 3D to 4D scanning systems now allows for scanning in motion. Several 4D scanner systems are available in current market including temporal-3dMD System (4D), Move 4D, and 3DCOPYSYSTEMS, which are based on the SL and photogrammetry technique (https://www.ibv.org/tecnologias/analisis-de-movimientos-4d/move-4d-3/; https://3dcopysystems.com/). Unfortunately, 4D scanners are impractical for routine use due to its expensive and occupied much space (Xu et al., 2021).

NOVEL PREDICTION MODEL BASED ON 3D ANTHROPOMETRY

More advanced prediction models for health assessment can be developed utilizing comprehensive anthropometric data acquired through 3D scanning. This includes exploring the intricate relationship between circumferences and the proportions of body segments, potentially leading to more precise predictions of varying body composition phenotypes, specifically body fat (Harbin 2017). A recent study by Harty et al. established a new prediction equation for BF% using machine learning and stepwise/lasso regression analyses based on 3D human body images and 4-component model anthropometric data (Harty et al., 2020). The outcomes exhibited high accuracy which was validated by DXA scans, suggesting a viable approach to identifying reliable anthropometric predictors within specific populations and larger samples. Löffler-Wirth et al. applied a neural network approach to identify 13 distinct body shape archetypes using 3D human body database from Germany (Löffler-Wirth et al., 2016). Similarly, Pleuss et al. established four subpopulations of homogenous body shape archetypes using principal components and cluster analysis based on 3D scanned anthropometry from USA (Pleuss et al., 2019). The correlation between body shape and fat distributions has also been explored through 3D anthropometry. The work of Piel, mapped the 3D body shape to the body composition and established a pixel-level prediction equation using stepwise regression (Piel 2017). Additionally, Lu et al. using Bayesian network to estimate the relationship between 3D body shape features and body fat, showed a high accuracy in BF% prediction (Lu et al., 2019). However, these studies predominantly focused on adult populations with relatively stable body shapes over time. Children and elderly, by contrast, undergo more pronounced overall body shape changes. Consequently, the prediction models based on the adult shape might be less accurate in children and elderly. Moreover. further investigation is still needed to determine which anthropometric measurement should be selected or how they should combine to create an optimal prediction equation considering diverse age and ethnic factors. It is important to note that the more accurate prediction model could be explored through in-depth data analysis, this doesn't imply that value of conventional anthropometric indicators derived from one-dimensional body measurements has diminished, as they continue to serve as valuable reference points in certain contexts.

THE POTENTIAL APPLICATION OF 3D SCANNING IN CLINICAL PRACTICE

3D scanning has received high acceptability in both research and clinical applications. With the development of new statistical modelling techniques, there is an opportunity to explore novel parameter of body shape features and link them with biological health outcomes. Furthermore, according to the concept of future healthcare, known as "P4 Health Continuum", including four aspects of predictive, preventive, personalized, and participatory (Sagner et al., 2017), the 3D scanning system appears to meet those requirements and holds potential for integration into healthcare services. The potential applications of 3D scanning in the future are discussed here, and the potential application of 3D scanning is illustrated in Figure 3.

The 3D scanner for whole-body scanning could be extended to various settings, such as schools, hospitals, fitness and health centers, for routine monitoring of body shape in a longitudinal way. The body shape change could result from exercise, nutrition, diet programs, or the natural aging process. By offering more accurate anthropometric data and allowing users to track changes over time, these changes could serve as strong motivators for individuals to persist in their efforts and enhance their body health or appearance. Medical professionals or trainers can effectively and conveniently assess individuals, enabling them to precisely identify how the surface shape of specific areas has changed over time.

Also, the 3D human body could offer significant value in the estimation of surface area, a crucial factor in drug dosage calculation. Traditionally, the surface area is calculated from weight and height, however, it is less accurate, especially in pediatric patients with obesity (Wells et al., 2008). Consequently, 3D scanning could provide an optimal estimation of surface area that substantially improves the precision of drug dosing, contributing to more effective and tailored medical treatments.

Additionally, the machine learning-based statistical prediction model for health assessment could be developed based on the large diverse database, to achieve the maximum benefit from anthropometric data. Conventional anthropometric indicators currently used for health assessment predominantly rely on one-dimensional data, potentially leading to the loss of some available details of human body. Therefore, the more sophisticated anthropometric indices could be explored from 3D human model using an advanced statistical model to evaluate health status.

On the other hand, static body posture assessment is currently possible through 3D scanning technology, allowing us to capture the entire body's posture, including assess the curvature of the cervical and spinal regions, pelvic alignment, leg and foot morphology, as well as body dimensions. However, dynamic body posture assessment, which considers posture during motion, has not yet been widely implemented. The application of a dynamic body posture assessment system has the potential to benefit various sectors. Such as, in clinical medical environments, it has the potential to enhance diagnostics and personalized treatment planning. In rehabilitation programs, it introduces a state-of-the-art tool for progress tracking and intervention refinement. Similarly, the sports and fitness field can leverage this assessment system to optimize training routines and reduce injury risks.

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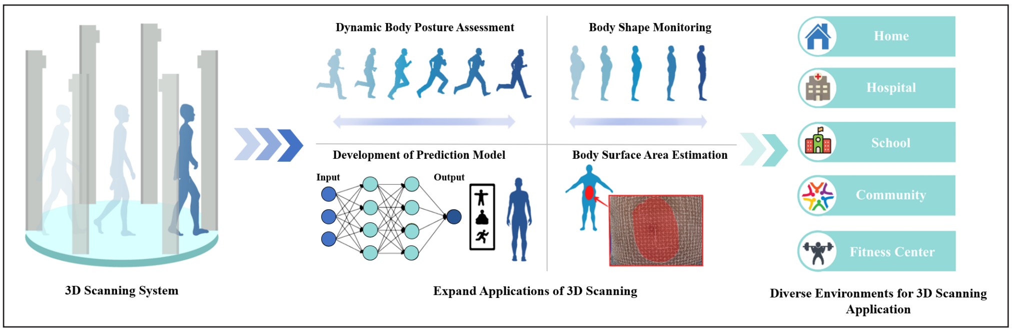

Figure 3 Further application of 3D scanning.

CONCLUSION

Anthropometric measurement plays a significant role in clinical settings, with the development of 3D scanning technology has innovated its collection and application. In this review, we analyzed the commonly used anthropometric indicators in clinical practice, including definition, calculation, and application in health assessment, as well as the current existing limitations among the Chinese population. Also, we suggested that regular anthropometric measurements could be included as part of routine health check-ups for children and adolescents, and more attention should be paid to aging-related anthropometrical changes. On the other hand, 3D scanning technology provides rich anthropometric data, which presents an opportunity to develop a more accurate prediction model to assess the body composition using state-of-the-art machine learning and statistical techniques. The further application of 3D scanning in clinical practice could be in those aspects: (1) body shape monitoring, (2) body posture assessment in both static and dynamic status, (3) creating a more accurate prediction model, and (4) body surface area prediction.

COMPETING INTERESTS

The authors have no competing interests to declare.

AUTHOR AFFILIATIONS

Meizi Wang
Department of Biomedical Engineering, The Hong Kong Polytechnic University, Hong Kong 999077, China

Yang Song
Department of Biomedical Engineering, The Hong Kong Polytechnic University, Hong Kong 999077, China

Xianglin Zhao
Department of Biomedical Engineering, The Hong Kong Polytechnic University, Hong Kong 999077, China

Yan Wang
Department of Biomedical Engineering, The Hong Kong Polytechnic University, Hong Kong 999077, China; Research Institute for Sports Science and Technology, The Hong Kong Polytechnic University, Hong Kong 999077, China

Ming Zhang
Department of Biomedical Engineering, The Hong Kong Polytechnic University, Hong Kong 999077, China; Research Institute for Sports Science and Technology, The Hong Kong Polytechnic University, Hong Kong 999077, China

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