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Evidence-Based Anthropometric Evaluation Methods for Obesity: A Systematic Review

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Abstract

Obesity assessment commonly relies on body mass index (BMI), although BMI does not directly reflect body-fat distribution or adiposity. This systematic review evaluated conventional and emerging anthropometric assessment methods for obesity, adiposity, and body composition, focusing on their validity, accuracy, agreement, reliability, diagnostic performance, and clinical usefulness.

Original, peer-reviewed English-language studies involving adults aged ⩾18 years were included. Studies evaluating anthropometric methods using validation, comparative validation, cross-sectional validation, prediction-model, or diagnostic-accuracy designs were considered. Methodological risk of bias was assessed using design-appropriate tools, including the JBI Critical Appraisal Checklist, QUADAS-3, and PROBAST, according to study design.

The included studies showed that conventional measures such as BMI, waist circumference, waist-to-height ratio, neck circumference, and skinfold thickness can provide useful information for obesity and adiposity assessment. Emerging three-dimensional optical scanning, smartphone-based imaging, and machine-learning approaches demonstrated promising agreement and accuracy compared with criterion methods such as dual-energy X-ray absorptiometry (DXA). However, differences in population characteristics, sample size, measurement protocols, reference standards, and external validation affected the generalizability of findings. Some prediction and diagnostic studies also demonstrated methodological concerns related to participant selection, reference standards, and model development.

Anthropometric assessment provides a practical, non-invasive, and relatively inexpensive approach to obesity and adiposity assessment. BMI and circumferential measures remain useful for screening, while central-adiposity indices and emerging digital technologies may provide complementary information. However, larger studies, standardized protocols, appropriate reference standards, and independent external validation are required before newer digital and machine-learning approaches can be widely implemented in clinical practice.

Categories: Therapeutics, Medical Education, Healthcare Technology
Keywords: adiposity, anthropometric assessment, body composition, digital anthropometry, machine learning, neck circumference, obesity, smartphone-based anthropometry, waist-to-height ratio

Introduction And Background

Obesity is a major global public health concern and is associated with substantial morbidity, premature mortality, and a wide range of cardiometabolic and other chronic health conditions [1,2]. The worldwide prevalence of obesity has increased substantially over recent decades, creating an urgent need for accurate, accessible, and clinically applicable approaches to identify excess adiposity, assess associated health risks, and monitor changes over time [1-3].

Body mass index (BMI), calculated as weight in kilograms divided by height in metres squared, remains one of the most widely used anthropometric measures for classifying overweight and obesity because of its simplicity, low cost, and ease of application in clinical and population settings [4]. However, BMI primarily reflects body size rather than adiposity and does not distinguish fat mass from lean mass or characterize regional fat distribution. Consequently, individuals with similar BMI values may have substantially different amounts and distributions of body fat and different health-risk profiles [5]. BMI is therefore useful for population-level screening and classification but may be insufficient for comprehensive assessment of individual adiposity.

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Adiposity refers primarily to the amount of body fat, whereas its distribution describes where adipose tissue is preferentially accumulated. Overall adiposity and fat distribution are not synonymous; central adiposity refers particularly to the accumulation of adipose tissue around the abdomen and trunk and is associated with cardiometabolic risk. Waist circumference (WC), waist-to-height ratio (WHtR), and waist-to-hip ratio (WHR) provide complementary information about central adiposity [5,6]. Interpretation of these measures may nevertheless be influenced by age, sex, ethnicity, anatomical measurement site, measurement protocol, and population characteristics.

The distinction between BMI, adiposity, central adiposity, and clinically meaningful obesity has become increasingly important with contemporary changes in the conceptualization of obesity. The 2025 Lancet Diabetes & Endocrinology Commission proposed distinguishing between preclinical and clinical obesity and emphasized that obesity assessment should extend beyond BMI-based classification to consideration of excess adiposity and its effects on health and physical function [7]. Within this framework, excess adiposity represents an important biological characteristic, whereas clinical obesity refers to a disease state in which excess adiposity is associated with objective manifestations or impairment of health and/or organ function [7]. Thus, BMI should not be considered synonymous with adiposity or central adiposity, and BMI alone should not be used as a direct measure of clinical obesity. A multidimensional assessment incorporating anthropometric measures, body-composition information, and relevant clinical manifestations may provide a more meaningful characterization of obesity.

Anthropometric methods remain clinically attractive because they are generally inexpensive, non-invasive, portable, and repeatable. These characteristics support their use in primary care, community programmes, epidemiological research, nutritional assessment, and resource-limited settings. However, their measurement performance depends on the specific parameter, measurement technique, anatomical site, population, and intended clinical purpose.

Recent technological advances have expanded anthropometric assessment beyond conventional manual measurements. Three-dimensional optical scanning, digital imaging, smartphone-based assessment, and machine-learning approaches may enable more automated acquisition of body dimensions and provide additional information on body shape and body-composition-related characteristics. These approaches complement conventional measures such as body mass index (BMI), waist circumference (WC), waist-to-height ratio (WHtR), waist-to-hip ratio (WHR), neck circumference, and skinfold thickness. The principal conventional and emerging approaches and their corresponding assessment domains are summarized in Figure *1*. However, the measurement performance of these emerging approaches may be influenced by device characteristics, image quality, body position, scanning conditions, software algorithms, reference methods, and population characteristics.

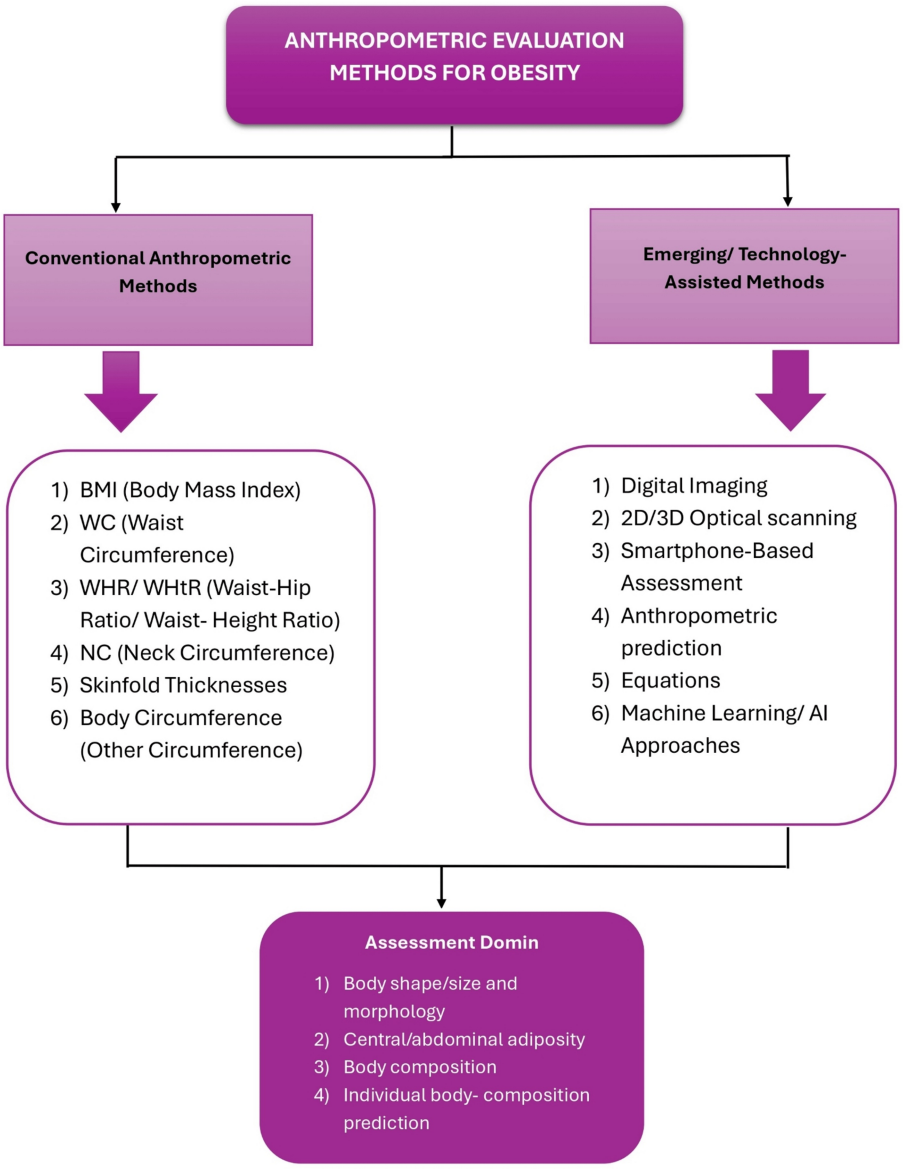


FIGURE 1: Classification of Conventional and Emerging Anthropometric Assessment Methods for Obesity and Their Principal Assessment Domains

Created by the authors using Microsoft Word. The conventional anthropometric methods and obesity-assessment concepts presented in the figure were based on previously published evidence [4-8]. The classification of emerging digital, three-dimensional, smartphone-based, and machine-learning approaches was developed by the authors based on the emerging anthropometric approaches evaluated in the primary studies included in this review.

BMI: Body Mass Index; WC: Waist Circumference; WHR: Waist-to-Hip Ratio; WHtR: Waist-to-Height Ratio; NC: Neck Circumference; AI: Artificial Intelligence; 2D: Two-Dimensional; 3D: Three-Dimensional.

Although advanced body-composition techniques can provide more detailed information, their routine clinical use may be limited by cost, equipment requirements, technical expertise, accessibility, and, for ionizing imaging modalities, radiation exposure. Anthropometric methods therefore remain important for obesity assessment, particularly where repeated, rapid, and low-cost measurements are required. However, their clinical value depends on appropriate validation against suitable reference or criterion methods and on understanding the extent to which measurement performance can be generalized across populations and clinical settings [6-8].

Despite the expanding range of conventional and technology-assisted anthropometric methods, important uncertainties remain regarding their measurement performance and clinical interpretation within the

contemporary conceptual framework of obesity. Existing studies have evaluated BMI, waist-based indices, skinfold thickness, anthropometric prediction equations, three-dimensional optical scanning, smartphone-based imaging, and machine-learning approaches using different populations, reference methods, measurement protocols, and outcome definitions. Consequently, evidence regarding validity, reliability, agreement, diagnostic accuracy, and predictive performance is heterogeneous and difficult to compare across methods. An important gap in the existing literature is the lack of an integrated synthesis comparing the measurement performance, limitations, and clinical applicability of conventional and emerging anthropometric approaches across these different domains. In particular, uncertainty remains regarding individual-level accuracy, the applicability of population-specific thresholds and prediction equations, and whether emerging digital approaches provide sufficiently reliable measurements for clinical use.

A systematic synthesis is therefore warranted to determine the measurement performance and clinical applicability of conventional and emerging anthropometric approaches for assessing obesity, excess adiposity, and body composition. This need is particularly relevant in light of contemporary definitions that distinguish excess adiposity from clinical obesity [7]. The present review is noteworthy because it brings together evidence from established anthropometric measures and emerging digital and computational approaches within a common evidence-based framework, allowing their respective strengths, limitations, measurement performance, and clinical applicability to be considered together. By synthesizing evidence from validation, diagnostic-accuracy, and prediction studies, the review also provides an educational framework for understanding which anthropometric methods may be appropriate for screening, adiposity assessment, central-adiposity assessment, and body-composition estimation, while highlighting the methodological factors that may limit their generalizability and clinical implementation.

Accordingly, the present systematic review aimed to critically evaluate the validity, reliability, agreement, diagnostic accuracy, and predictive performance of anthropometric methods used to assess obesity, excess adiposity, and body composition. The review examined conventional measures, including BMI, WC, WHR, WHtR, neck circumference, and skinfold thickness, as well as anthropometric prediction equations and emerging digital, three-dimensional, smartphone-based, and machine-learning approaches. By synthesizing their measurement performance, limitations, and clinical applicability, this review sought to identify evidence-based and purpose-specific approaches for the assessment of obesity and adiposity.

Review

Methodology

Study Design

This systematic review aimed to critically assess and synthesize evidence on conventional and emerging anthropometric methods for evaluating overweight, obesity, adiposity, and body composition in adults. Conventional methods included body mass index, waist circumference, waist-to-height ratio, waist-to-hip ratio, neck circumference, and skinfold thickness, while emerging approaches included anthropometric equations, three-dimensional optical scanning, and digital or smartphone-based anthropometry. The review focused on validity, accuracy, reliability, agreement, reproducibility, diagnostic performance, and clinical applicability, with appropriate reference or comparator methods considered where applicable. The review was conducted and reported in accordance with the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) 2020 statement [9]. Due to substantial heterogeneity in anthropometric methods, study populations, reference methods, and reported outcomes, the findings were synthesized narratively rather than quantitatively.

This systematic review was prospectively registered in the International Prospective Register of Systematic Reviews (PROSPERO) under registration number CRD420261532315 on 7 October 2026. The registered review title is Evidence-Based Anthropometric Evaluation Methods for Obesity: A Systematic Review. The registration was completed before the final synthesis of the review findings.

Information Sources

A comprehensive electronic literature search was conducted in PubMed/MEDLINE, Scopus, Web of Science, Embase, Cochrane Library, and Google Scholar. The electronic database searches were conducted through August 2026, and studies published from January 2019 through August 2026 were considered eligible. Additional eligible studies were identified through reference-list screening and forward citation tracking of relevant systematic reviews, meta-analyses, and key primary studies. Systematic reviews and meta-analyses were used only as supplementary sources for identifying potentially eligible primary studies and were not included as primary evidence in the final synthesis.

Search Strategy

The search strategy used Boolean operators AND and OR to combine terms related to obesity or adiposity, anthropometric assessment, and measurement or diagnostic performance. Key search terms included obesity, overweight, adiposity, body composition, anthropometry, body mass index, waist circumference,

waist-to-height ratio, waist-to-hip ratio, neck circumference, skinfold thickness, anthropometric equations, digital anthropometry, three-dimensional anthropometry, validity, accuracy, reliability, agreement, reproducibility, and diagnostic accuracy. Searches were restricted to English-language studies involving adults aged ⩾18 years, according to the predefined eligibility criteria. Eligible study designs included validation, comparative validation, cross-sectional validation, diagnostic-accuracy, and prospective validation studies, as specified in the study protocol. The complete database-specific search strategies are provided in Table *1*.

Database	Search Strategy
PubMed/MEDLINE (Medical Literature Analysis and Retrieval System Online)	("Obesity"[MeSH] OR obesity OR overweight OR adiposity OR "body composition") AND ("Anthropometry"[MeSH] OR anthropometr* OR "body mass index" OR BMI OR "waist circumference" OR "waist-to-height ratio" OR WHtR OR "skinfold thickness" OR "anthropometric equation*" OR "digital anthropometry" OR "3D anthropometry") AND (valid* OR accuracy OR reliability OR agreement OR "diagnostic accuracy" OR sensitivity OR specificity OR ROC OR AUC)
Scopus	TITLE-ABS-KEY ((obesity OR overweight OR adiposity OR "body composition") AND (anthropometr* OR "body mass index" OR BMI OR "waist circumference" OR WHtR OR "skinfold thickness" OR "anthropometric equation*" OR "digital anthropometry" OR "3D anthropometry") AND (valid* OR accuracy OR reliability OR agreement OR "diagnostic accuracy" OR sensitivity OR specificity OR ROC OR AUC))
Web of Science	TS=((obesity OR overweight OR adiposity OR "body composition") AND (anthropometr* OR "body mass index" OR BMI OR "waist circumference" OR WHtR OR "skinfold thickness" OR "anthropometric equation*" OR "digital anthropometry" OR "3D anthropometry") AND (valid* OR accuracy OR reliability OR agreement OR "diagnostic accuracy" OR sensitivity OR specificity OR ROC OR AUC))
Embase	('obesity'/exp OR obesity:ti,ab OR overweight:ti,ab OR adiposity:ti,ab OR 'body composition':ti,ab) AND ('anthropometry'/exp OR anthropometr*:ti,ab OR 'body mass index':ti,ab OR bmi:ti,ab OR 'waist circumference':ti,ab OR 'waist-to-height ratio':ti,ab OR 'skinfold thickness':ti,ab OR 'anthropometric equation*':ti,ab OR 'digital anthropometry':ti,ab OR '3d anthropometry':ti,ab) AND (valid*:ti,ab OR accuracy:ti,ab OR reliability:ti,ab OR agreement:ti,ab OR 'diagnostic accuracy':ti,ab OR sensitivity:ti,ab OR specificity:ti,ab OR roc:ti,ab OR auc:ti,ab)
Cochrane Library	(obesity OR overweight OR adiposity OR "body composition") AND (anthropometry OR "body mass index" OR BMI OR "waist circumference" OR WHtR OR "skinfold thickness" OR "anthropometric equation*" OR "digital anthropometry" OR "3D anthropometry") AND (validity OR accuracy OR reliability OR agreement OR "diagnostic accuracy" OR sensitivity OR specificity OR ROC OR AUC)
Google Scholar	"obesity" AND ("anthropometry" OR "body mass index" OR BMI OR "waist circumference" OR "waist-to-height ratio" OR WHtR OR "skinfold thickness" OR "digital anthropometry" OR "3D anthropometry") AND (validation OR validity OR accuracy OR reliability OR agreement OR "diagnostic accuracy")

TABLE 1: Database-specific search strategies

MeSH: Medical Subject Headings; MEDLINE: Medical Literature Analysis and Retrieval System Online; BMI: Body Mass Index; WHR: Waist-to-Hip Ratio; WHtR: Waist-to-Height Ratio; ROC: Receiver Operating Characteristic; AUC: Area Under the Curve; PEDro: Physiotherapy Evidence Database; 3D: Three-Dimensional; OR: Boolean operator used to combine alternative or related search terms; AND: Boolean operator used to combine different search concepts; TS: Topic search field in Web of Science; TITLE-ABS-KEY: Title, Abstract, and Keywords fields in Scopus, Heading, /exp: Embase exploded subject heading, including narrower related terms; :ti,ab: Embase search fields for title and abstract; (*): Truncation/wildcard symbol used to retrieve different word endings; (" "): Quotation marks used to search an exact phrase.

In addition to the electronic database searches, the reference lists of relevant systematic reviews, meta-analyses, and key primary studies were screened to identify potentially eligible studies that may not have been retrieved through the database searches. Forward citation tracking of relevant studies was also performed where applicable. Systematic reviews and meta-analyses were not included as primary evidence in the final synthesis; rather, they were used as supplementary sources to identify potentially eligible primary studies and assess the completeness of the literature search.

Eligibility criteria

Inclusion Criteria

Original, peer-reviewed papers involving adults (⩾18 years old), including normal-weight, overweight, and obese participants, published in English between January 2019 and August 2026 were eligible for inclusion. Studies assessing one or more conventional or emerging anthropometric techniques for determining body composition, obesity, or adiposity were considered eligible. Eligible studies reported outcomes related to validity, accuracy, agreement, reliability, repeatability, diagnostic performance, or clinical utility. Included

study designs comprised validation, cross-sectional validation, comparative validation, diagnostic-accuracy, and prospective validation studies using suitable reference or comparator techniques.

Potentially relevant primary studies identified through previous systematic reviews were assessed using the same predefined eligibility criteria as studies identified through the electronic database searches. Studies were eligible only when the anthropometric method was directly evaluated in relation to obesity, overweight, excess adiposity, or body composition in adults and relevant validation, accuracy, agreement, reliability, diagnostic-performance, or prediction outcomes were reported.

Exclusion Criteria

Review articles, systematic reviews, meta-analyses, conference abstracts, editorials, letters, case reports, case series, research protocols, non-English publications, studies involving animals or cadavers, and studies involving participants under 18 years were excluded. Studies were also excluded when they did not assess an anthropometric method for evaluating body composition, obesity, or adiposity; did not report relevant evaluation or validation outcomes; had unavailable full text; were duplicate publications; used substantially overlapping datasets; or provided insufficient methodological information.

The inclusion and exclusion criteria are summarized in Table *2*.

Category	Inclusion Criteria	Exclusion Criteria
Study Population	Adults ≥18 years	<18 years; pregnant women; animals/cadavers
Study Design	Original peer-reviewed validation, cross-sectional validation, comparative-validation, prospective validation, or diagnostic-accuracy studies	Reviews; meta-analyses; protocols; case reports/series; editorials; letters; conference abstracts
Anthropometric Evaluation method	BMI; WC; WHR; WHtR; NC; skinfold thickness; anthropometric equations; digital/3D anthropometry	No relevant anthropometric method
Evaluation purpose	Evaluation of obesity, overweight, adiposity, or body composition	Unrelated to obesity, adiposity, overweight, or body-composition evaluation
Evaluation Outcomes	Validity; accuracy; reliability; agreement; reproducibility; diagnostic performance	No relevant evaluation or validation outcome
Reference standard	Appropriate reference, criterion, or comparator method where applicable	Insufficient information to evaluate the anthropometric method
Data availability	English; full-text; peer-reviewed; 2019-2026; Unique study population/dataset	Non-English; unavailable full text; non-peer-reviewed; duplicate publication; substantially overlapping dataset reporting the same relevant outcomes

TABLE 2: Eligibility criteria of the included studies.

BMI: Body Mass Index; WC: Waist Circumference; WHR: Waist-to-Hip Ratio; WHtR: Waist-to-Height Ratio; NC: Neck Circumference; 3D: Three-Dimensional.

Selection Process

Two reviewers independently screened titles and abstracts after duplicate records were removed. Potentially eligible reports were retrieved for full-text assessment and evaluated according to the predefined inclusion and exclusion criteria. Disagreements between reviewers were resolved through discussion and consensus. The PRISMA 2020 flow diagram was used to present the study-selection process [9].

Data Collection Process

A standardized data-extraction form was used by the reviewers to independently extract information from the eligible studies. Extracted data were cross-checked for accuracy, and disagreements were resolved through discussion and consensus.

Data Items

The following information was extracted from each included study: author and publication year, study design, participant characteristics, anthropometric method or measurement technology, parameter or anatomical site assessed, reference or comparator method, evaluation purpose, outcome measures, principal validity or diagnostic findings, and reported advantages and limitations.

Quality Assessment

The methodological quality and risk of bias of the included studies were assessed using study-design-specific appraisal tools. The appraisal tool was selected according to the primary methodological purpose of each study. The Joanna Briggs Institute (JBI) Critical Appraisal Checklist for Analytical Cross-Sectional Studies [10] was used for cross-sectional validation studies primarily evaluating measurement validity, reliability, or agreement. For these studies, each applicable criterion was judged as "Yes," "No," "Unclear," or "N/A" based on the information reported in the study. The appraisal was performed at the criterion level rather than by applying an arbitrary numerical score. Overall methodological concern was determined from the pattern of responses across the applicable criteria, with particular attention to participant selection, measurement validity and reliability, identification and management of confounding factors, and appropriateness of statistical analysis. Studies with predominantly satisfied criteria but one or more areas of insufficient reporting were classified as having "Some Concerns." The Prediction model Risk Of Bias Assessment Tool (PROBAST) [11] was used for studies involving the development or evaluation of prediction or estimation models. The Quality Assessment of Diagnostic Accuracy Studies-3 (QUADAS-3) tool [12] was used for studies specifically designed to evaluate the diagnostic accuracy of an anthropometric index against a predefined target condition. The allocation of individual studies to each appraisal tool is shown in Tables *4*-*6*, with JBI applied to the cross-sectional validation studies, PROBAST to prediction or estimation-model studies, and QUADAS-3 to diagnostic-accuracy studies. Risk-of-bias assessments were performed independently by two reviewers, and disagreements were resolved through discussion and consensus. The criterion-level judgments and overall assessments were considered when interpreting the findings and are presented in Tables *4*-*6*.

Synthesis Methods

Quantitative meta-analysis was not performed because of substantial clinical and methodological heterogeneity across the included studies, including variations in research populations, anthropometric techniques, measuring tools, reference or comparator methods, and reported outcomes. Although studies were descriptively organized according to their principal anthropometric approach, methodological characteristics, and study design, no formal quantitative comparison or pooled estimate was performed across anthropometric methods, outcomes, reference standards, or study designs. Therefore, the findings were narratively synthesized in accordance with the Synthesis Without Meta-analysis (SWiM) reporting guidelines [13]. The narrative synthesis was organized according to conventional anthropometric methods, emerging technology-assisted methods, and the primary measurement domains assessed in each study. Outcomes prioritized for synthesis included validity, accuracy, reliability, agreement, reproducibility, diagnostic performance, and prediction or estimation performance, as applicable to the individual study design. Differences in reference or criterion standards were considered when interpreting study findings and were not treated as directly equivalent across studies. Risk-of-bias assessments were considered when interpreting the strength, consistency, and clinical applicability of the findings, with greater caution applied to findings from studies with higher methodological concerns. For diagnostic-accuracy and prediction or estimation-model studies, relevant performance measures were summarized where reported; these included area under the receiver operating characteristic curve (AUC), sensitivity, specificity, and 95% confidence intervals for diagnostic studies, and discrimination, calibration, prediction error, and external validation measures for prediction or estimation models. The revised statistical synthesis and reporting will be subjected to additional review by a statistician before final resubmission to ensure the appropriateness of the decision not to pool the results and the reporting of diagnostic and prediction-model performance measures.

Results

A comprehensive literature search was conducted in PubMed/MEDLINE, Scopus, Web of Science, Embase, Cochrane Library, and Google Scholar. A total of 916 records were identified, of which 276 duplicate records were removed, leaving 640 records for title and abstract screening. Following screening, 565 records were excluded, and 75 reports were sought for retrieval. Of these, three reports could not be retrieved, leaving 72 full-text reports for eligibility assessment. After full-text assessment, 53 reports were excluded for the following reasons: wrong study design (n = 15), absence of validation, accuracy, or reliability assessment (n = 12), wrong population (n = 8), inappropriate outcome or anthropometric assessment method (n = 7), publication outside the predefined 2019-2026 period (n = 5), duplicate or overlapping study population (n = 3), and insufficient relevant data or full-text information (n = 3). Finally, 19 studies met the predefined eligibility criteria and were included in the systematic review. The study-selection process is presented in the PRISMA 2020 flow diagram (Figure *2*).

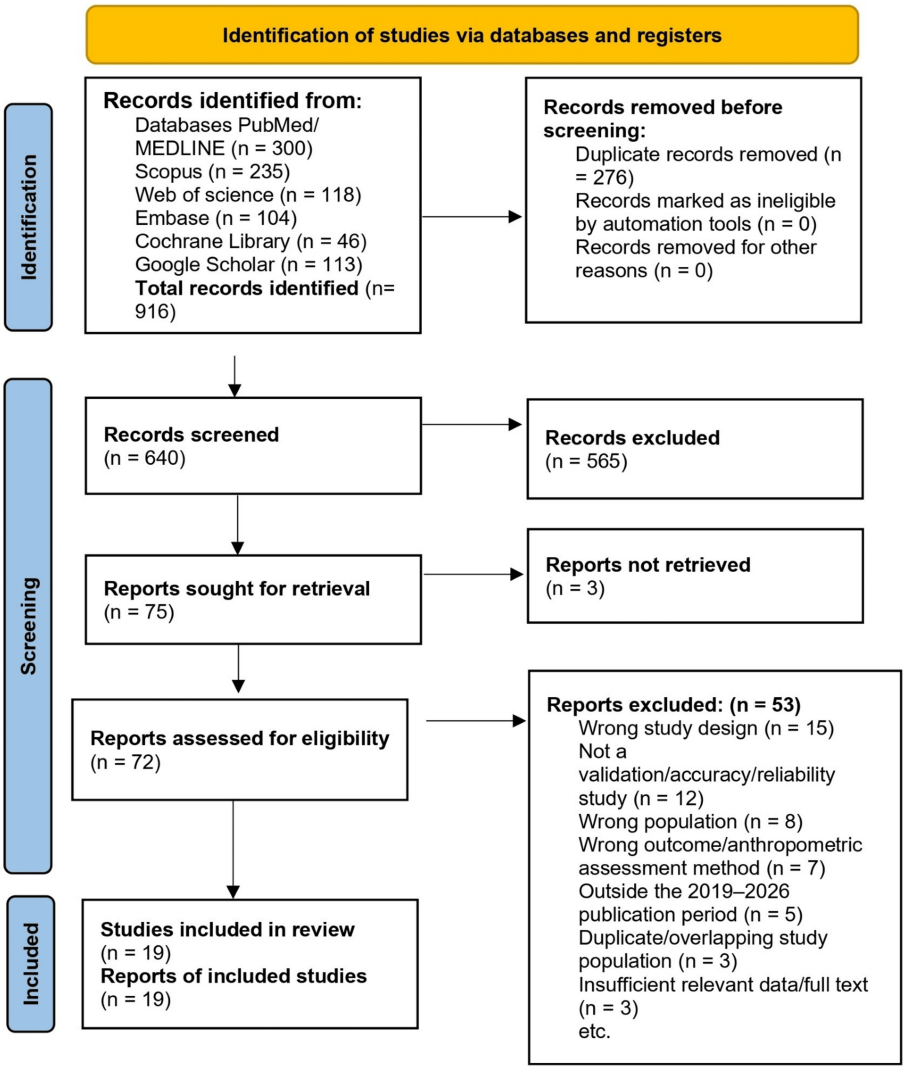


FIGURE 2: PRISMA flow diagram.

PRISMA: Preferred Reporting Items for Systematic Reviews and Meta-Analyses

The 19 included studies evaluated one or more aspects of anthropometric measurement performance, including validity, accuracy, reliability, agreement, reproducibility, diagnostic performance, or prediction performance, depending on the study design and assessment method. The specific outcomes assessed in each study are presented in Table *3*.

No.	Study	Study Design	Population	Assessment Category	Anthropometric Method / Technology	Parameter / Anatomical Site Assessed	Reference / Criterion Method	Outcome Assessed	Main Finding
1	Castro-Porras et al. (2019) [14]	Cross-sectional validation	275 Mexican adults	Conventional / parametric	Anthropometry-based equation; BMI; % body fat	Height, weight, BMI and body-fat-related parameters	Air-displacement plethysmography	Body-fat percentage; fat-free mass; obesity discrimination	Anthropometric equation provided a simple and inexpensive approach to estimating body fat.
2	Tinsley et al. (2020) [15]	Cross-sectional validation	Adults	Emerging / advanced	3D optical scanning	Whole-body dimensions and circumferences	DXA; ADP	Circumferences; body volume	3D optical scanning provided rapid and precise body measurements, with performance varying between scanners.
3	Harty et al. (2020) [16]	Validation	179 adults	Emerging / advanced	3D optical imaging + machine learning	Whole-body 3D body-shape parameters	DXA; 4-component model	Body-fat percentage	Machine-learning models using 3D imaging demonstrated promising body-fat estimation.
	Tinsley et al.	Cross-		Emerging /	Four 3D optical	Whole-body dimensions,	4-component	Fat mass; fat-free mass;	3D scanners demonstrated potential for body-

4	(2020) [17]	sectional validation	171 adults	advanced	scanners	body volume and body shape	model	body volume; body shape	composition assessment, although device-specific differences were observed.
5	Kogure et al. (2020) [18]	Cross-sectional validation	170 Brazilian women	Conventional / parametric	Skinfold thickness	Skinfold sites / subcutaneous adiposity	DXA; BIA	Body-fat percentage; measurement reproducibility	Skinfold methods showed acceptable reproducibility but were not interchangeable with DXA.
6	Wong et al. (2021) [19]	Validation	Adults	Emerging / advanced	3D optical scanning	Whole-body 3D anthropometric/body-shape parameters	DXA	Fat mass; fat-free mass; visceral fat	Pose-independent 3D models improved body-composition prediction.
7	Kawaji & Fontanilla (2021) [20]	Validation study	221 overweight/obese Filipino adults	Conventional / parametric	Waist circumference	Waist circumference	BIA	Visceral adiposity	Waist circumference protocols provided a practical approach to estimating visceral adiposity.
8	Nana et al. (2022) [21]	Cross-sectional comparative validation	Adults aged 18–65 years	Emerging / advanced	2D smartphone imaging	Digitally derived anthropometric dimensions	DXA; BIA	Anthropometric measures; body-fat percentage; fat-free mass	Smartphone-based assessment showed potential for accessible body-composition assessment.
9	Bennett et al. (2022) [22]	Cross-sectional validation	188 adults	Emerging / advanced	Commercial 3D optical scanning	Whole-body dimensions and body volume	DXA; manual anthropometry	Body volume; fat mass; fat-free mass	3D scanning provided rapid automated assessment of total and regional body composition.
10	Guzmán-García et al. (2022) [23]	Cross-sectional diagnostic accuracy	635 working adults	Conventional / parametric	WHtR, WC, WHR, BMI	Waist, hip and height-derived indices	Clinical/biochemical assessment	Metabolically healthy obesity; diagnostic performance	WHtR demonstrated strong diagnostic performance among the evaluated anthropometric indices.
11	Masmoudi et al. (2023) [24]	Validation	20 adults	Emerging / advanced	CT-based mobile application	Waist circumference	Tape measurement	Waist circumference	Mobile-app estimation of waist circumference showed promising preliminary accuracy.
12	Wong et al. (2023) [25]	Cross-sectional validation	Adults	Emerging / advanced	3D optical imaging	Whole-body 3D anthropometric/body-shape parameters	DXA	Fat mass; fat-free mass; visceral adipose tissue; body-fat percentage	3D optical imaging showed good body-composition estimation across BMI, age, and ethnic groups.
13	Mecherques-Carini et al. (2024) [26]	Cross-sectional validation	Young adults	Conventional / parametric	BMI; body-fat percentage; fat mass	Height, weight and body-composition-related parameters	DXA; BIA	Fat mass; body-fat estimation	Anthropometric measures showed agreement with criterion methods.
14	McCarthy et al. (2024) [27]	Prospective validation	44 adults	Emerging / advanced	3D smartphone application	Waist and hip dimensions	DXA; manual measurements	Waist/hip measures; visceral adiposity risk	Smartphone-based 3D assessment showed promising agreement with conventional measurements.
15	Nair et al. (2024) [28]	Cross-sectional diagnostic	362 women	Conventional / parametric	Neck circumference; BMI; WC; WHR	Neck, waist and hip measurements; height/weight-derived indices	BIA	Obesity screening	Neck circumference provided a simple screening measure, although generalizability was limited.
16	Florez et al. (2024) [29]	Validation	Adults	Emerging / advanced	Mobile-phone 3D imaging	Whole-body 3D anthropometric/body-composition parameters	DXA; 4-component model	Body-fat percentage; fat mass; fat-free mass	Mobile 3D imaging showed potential for body-composition estimation, although individual-level agreement varied.
17	Birk et al. (2025) [30]	Validation	Indian adults	Emerging / advanced	Anthropometry + machine learning	Anthropometric parameters used in predictive equations	DXA	Fat mass; body composition	Machine-learning equations improved body-composition estimation but require external validation.
18	Lin et al. (2026) [31]	Cross-sectional diagnostic	10,747 US adults	Conventional / parametric	BMI; WC; WHtR; WHR	Weight, height, waist and hip measurements	DXA	Excess adiposity; diagnostic performance	BMI and waist-based measures demonstrated varying ability to identify excess adiposity.
19	Theodorou et al. (2026) [32]	Prospective diagnostic	330 Greek women	Conventional / parametric	BMI	Weight and height	DXA	Adiposity classification	BMI showed useful screening performance but remained subject to population-specific misclassification.

TABLE 3: Characteristics of Included Studies and Anthropometric Assessment Methods

BMI: Body Mass Index; %FM: Percentage Fat Mass; FFM: Fat-Free Mass; DXA: Dual-Energy X-ray Absorptiometry; BOD POD®: Body Composition Tracking System; ADP: Air Displacement Plethysmography; BF%: Body Fat Percentage; 4C: Four-Component Model; 3D: Three-Dimensional; BIS: Bioelectrical Impedance Spectroscopy; WC: Waist Circumference; WHO: World Health Organization; NIH: National Institutes of Health; CT: Computed Tomography; MRI: Magnetic Resonance Imaging; 2D: Two-Dimensional; WHtR: Waist-to-Height Ratio; WHR: Waist-to-Hip Ratio; MHO: Metabolically

Healthy Obesity; HC: Hip Circumference; BIA: Bioelectrical Impedance Analysis; AI: Artificial Intelligence; US: United States; DEXA/DXA: Dual-Energy X-ray Absorptiometry.

Note: Studies are grouped according to the principal anthropometric assessment approach evaluated. Conventional methods include BMI, waist-based measures, neck circumference, and skinfold thickness, whereas emerging or technology-assisted methods include anthropometric prediction equations, three-dimensional optical scanning, smartphone-based imaging, digital imaging, and machine-learning approaches. Reference or criterion methods varied across studies according to the measurement outcome being evaluated.

The 19 included studies comprised different study designs, including cross-sectional validation, diagnostic-accuracy, and prediction or estimation-model studies. Methodological quality and risk of bias were therefore assessed using design-specific appraisal tools, and the findings were synthesized narratively because of the heterogeneity across study designs, assessment methods, reference standards, and outcomes.

The included studies differed substantially in study design, anthropometric measurement methods, reference or criterion standards, population characteristics, and outcome measures. Conventional anthropometric measures and emerging digital or technology-assisted approaches were therefore considered according to their respective measurement domains. Because these methods assess different aspects of adiposity and body composition and were evaluated using different reference standards and outcome measures, their findings were synthesized narratively rather than quantitatively compared across all studies. Where reported in the original studies, quantitative performance measures were extracted and summarized according to the applicable study design. These included sensitivity, specificity, area under the receiver operating characteristic curve (AUC), agreement measures, reliability coefficients, and corresponding confidence intervals. For diagnostic-accuracy studies, diagnostic performance measures were reported descriptively where available. Because the reported measures, thresholds, target conditions, reference standards, populations, and assessment methods varied across studies, these quantitative estimates were not statistically pooled.

Risk of Bias Assessment

The methodological quality and risk of bias of the included studies were evaluated using a structured eight-domain appraisal approach addressing participant selection, study setting, anthropometric measurement validity and reliability, objective and standardized assessment criteria, potential confounding, outcome measurement, and statistical analysis. Eight studies were assessed: Tinsley et al. (2020) [15], Tinsley et al. (2020) [17], Kogure et al. (2020) [18], Nana et al. (2022) [21], Bennett et al. (2022) [22], Wong et al. (2023) [25], Mecherques-Carini et al. (2024) [26], and McCarthy et al. (2024) [27]. All eight studies received “Yes” judgments for Q1-Q4 and Q7-Q8, whereas Q5 and Q6 were rated “Unclear” in all studies. Consequently, all eight studies were classified as having “Some Concerns.” Detailed criterion-level assessments are presented in Table *4*.

S. No.	Author (Year)	Q1. Were the inclusion criteria clearly defined?	Q2. Were the study participants and setting adequately described?	Q3. Was the anthropometric method measured in a valid and reliable manner?	Q4. Were objective and standardized criteria used to assess obesity, adiposity, or body composition?	Q5. Were potential confounding factors identified?	Q6. Were appropriate methods used to address identified confounding factors?	Q7. Were the anthropometric/body-composition outcomes measured in a valid and reliable manner?	Q8. Was appropriate statistical analysis used to evaluate validity, agreement, reliability, or diagnostic performance?	Overall risk of bias
1.	Tinsley et al. (2020) [15]	Yes	Yes	Yes	Yes	Unclear	Unclear	Yes	Yes	Some Concerns
2.	Tinsley et al. (2020) [17]	Yes	Yes	Yes	Yes	Unclear	Unclear	Yes	Yes	Some Concerns
3.	Kogure et al. (2020) [18]	Yes	Yes	Yes	Yes	Unclear	Unclear	Yes	Yes	Some Concerns
4.	Nana et al. (2022) [21]	Yes	Yes	Yes	Yes	Unclear	Unclear	Yes	Yes	Some Concerns
5.	Bennett et al. (2022) [22]	Yes	Yes	Yes	Yes	Unclear	Unclear	Yes	Yes	Some Concerns
6.	Wong et al. (2023) [25]	Yes	Yes	Yes	Yes	Unclear	Unclear	Yes	Yes	Some Concerns
7.	Mecherques-Carini et al. (2024) [26]	Yes	Yes	Yes	Yes	Unclear	Unclear	Yes	Yes	Some Concerns
8.	McCarthy et al. (2024) [27]	Yes	Yes	Yes	Yes	Unclear	Unclear	Yes	Yes	Some Concerns

TABLE 4: Risk-of-Bias Assessment of Included Cross-Sectional Validation Studies Using the JBI Critical Appraisal Checklist for Analytical Cross-Sectional Studies.

Assessment categories: Yes = criterion satisfied; No = criterion not satisfied; Unclear = insufficient information to determine whether the criterion was satisfied; N/A = criterion not applicable to the study design.

Overall risk-of-bias interpretation: Some Concerns = one or more appraisal criteria had insufficient information or potential methodological concerns that prevented classification as low risk of bias.

The “Unclear” ratings for Q5 and Q6 reflected insufficient information regarding the identification of relevant confounding factors and the strategies used to address their potential influence. This indicates limited reporting clarity rather than confirmation that confounding was present or that the studies were methodologically poor. The overall “Some Concerns” classification therefore reflected uncertainty arising from incomplete reporting in these domains, while the remaining appraisal criteria were predominantly satisfied.

Six studies were assessed using PROBAST across the domains of participant selection, predictors, outcome, and analysis. Three studies, Castro-Porras et al. (2019) [14], Wong et al. (2021) [19], and Florez et al. (2024) [29], were judged to have a low overall risk of bias, with low risk across all four domains. Harty et al. (2020) [16] and Masmoudi et al. (2023) [24] were judged to have a high overall risk of bias because of concerns in the predictor and analysis domains, with additional concerns regarding participant selection in Masmoudi et al. (2023) [24]. Birk et al. (2025) [30] was also classified as having a high overall risk of bias, primarily because of participant-selection concerns. Thus, three studies were rated low risk and three high risks, indicating that although several prediction models demonstrated satisfactory methodological quality, concerns regarding participant selection, predictor assessment, and analytical methods may limit confidence in the generalizability of some models. Detailed PROBAST assessments are presented in Table *5*.

S. No.	Author (Year)	Participant Selection	Predictors	Outcome	Analysis	Overall Risk of Bias
1.	Castro-Porras et al. (2019) [14]	Low	Low	Low	Low	Low Risk
2.	Harty et al. (2020) [16]	Low	High	Low	High	High Risk
3.	Wong et al. (2021) [19]	Low	Low	Low	Low	Low Risk
4.	Masmoudi et al. (2023) [24]	High	High	Low	High	High Risk
5.	Florez et al. (2024) [29]	Low	Low	Low	Low	Low Risk
6.	Birk et al. (2025) [30]	High	Low	Low	Low	High Risk

TABLE 5: Risk-of-Bias Assessment of Included Prediction-Model Studies Using PROBAST

Low risk: Methodological limitations are unlikely to substantially affect the study's prediction-model findings.

High risk: Important methodological concerns may affect confidence in the prediction-model findings.

Unclear risk: Insufficient reporting prevents a confident judgment.

The risk of bias of five diagnostic-accuracy studies was assessed using the QUADAS-3 tool across four domains: participants, index test, target condition, and analysis. Kawaji and Fontanilla (2021) [20] were judged to have a high risk of bias in the participant and target-condition domains, although the index-test and analysis domains were rated low, resulting in an overall high risk of bias. Guzmán-García et al. (2022) [23] demonstrated low risk in participant selection, index testing, and analysis, but high risk in the target-condition domain and were therefore classified as having an overall high risk of bias. Nair et al. (2024) [28] similarly showed high risk in the participant and target-condition domains, with low risk for the index test and analysis, resulting in an overall high risk of bias. In contrast, Theodorou et al. (2026) [32] and Lin et al. (2026) [31] were rated as having low risk of bias across all four domains and were classified as having a low overall risk of bias. Overall, three studies were judged to have a high risk of bias, whereas two studies demonstrated a low risk of bias. The principal concerns were related to participant selection and the definition or assessment of the target condition, while the index-test and analysis domains were generally rated as low risk. Detailed results of the QUADAS-3 assessment are presented in Table *6*.

S. No.	Author (Year)	Participants–Risk of Bias	Index Test–Risk of Bias	Target Condition–Risk of Bias	Analysis–Risk of Bias	Overall Risk of Bias
1.	Kawaji & Fontanilla (2021) [20]	High	Low	High	Low	High Risk
2.	Guzmán-García et al. (2022) [23]	Low	Low	High	Low	High Risk
3.	Nair et al. (2024) [28]	High	Low	High	Low	High Risk
4.	Theodorou et al. (2026) [32]	Low	Low	Low	Low	Low Risk
5.	Lin et al. (2026) [31]	Low	Low	Low	Low	Low Risk

TABLE 6: Risk-of-Bias Assessment of Included Diagnostic-Accuracy Studies Using the QUADAS-3 Tool

Discussion

Principal Findings

This systematic review analysed 19 studies on the validity, reliability, agreement, and diagnostic performance of various anthropometric methods for assessing obesity and body composition. It included traditional measures like BMI, waist circumference, and skinfold thickness, as well as newer techniques such as 2D/3D imaging and machine-learning approaches. The review found that while anthropometric methods

are useful, their accuracy depends on the measurement method, population, protocol, and reference standard. Therefore, the evidence supports a standardized and multimodal approach rather than reliance on a single anthropometric measure.

Previous systematic reviews have examined individual anthropometric domains and emerging technologies in greater depth and may have included larger numbers of studies within their respective areas. However, direct comparison of study numbers across reviews is not appropriate because eligibility criteria, populations, outcomes, study designs, and clinical objectives differ. The present review deliberately applied a specific obesity- and adiposity-focused eligibility framework and integrated evidence across conventional and emerging anthropometric approaches. The 19 included studies therefore represent studies that fulfilled the predefined criteria of this review rather than an attempt to reproduce the study populations of broader domain-specific systematic reviews.

Heterogeneity of the Included Evidence

The included studies demonstrated substantial methodological heterogeneity with respect to study design, anthropometric measurement methods, reference or criterion standards, population characteristics, and outcome measures. Conventional anthropometric measures, such as BMI and waist-based indices, were evaluated alongside emerging digital, three-dimensional, smartphone-based, and machine-learning approaches. These methods assess different aspects of adiposity and body composition and were evaluated using different validation frameworks and reference standards, limiting the comparability of their findings across studies. Therefore, the evidence was synthesized according to measurement domains and methodological characteristics, with study-design-specific risk-of-bias assessments considered separately.

BMI and Conventional Anthropometric Assessment

BMI remains an important first-line measure because it is inexpensive, rapid, non-invasive, and easily applicable in clinical and population settings. However, BMI reflects body size rather than directly measuring adiposity and cannot distinguish fat mass from lean mass or adequately characterize regional fat distribution [4,5]. Theodorou et al. (2026) [32] evaluated BMI against DXA-based adiposity assessment and demonstrated its usefulness while also highlighting limitations related to adiposity classification, age, and population characteristics. Lin et al. (2026) [31] further evaluated BMI, WC, WHtR, and WHR against DXA-derived excess adiposity in 10,747 adults, providing contemporary evidence regarding the diagnostic performance of commonly used anthropometric measures.

These findings reinforce the distinction between body-size classification and adiposity assessment. Individuals with similar BMI values may have substantially different amounts and distributions of adipose and lean tissue [4,5]. Accordingly, BMI should primarily be considered a practical screening measure and interpreted together with complementary measures when more detailed assessment of adiposity is required.

Waist-Based Anthropometric Indices for Central Adiposity Assessment

Waist-based measures, including WC, WHR, and WHtR, provide information about central adiposity that complements BMI. WC is recognized as an important clinical indicator of abdominal adiposity and cardiometabolic risk [7]. Kawaji and Fontanilla (2021) [20] demonstrated that WC measurement was simple, inexpensive, and non-invasive but also showed that measurement protocol and anatomical landmark selection can influence its performance. Guzmán-García et al. (2022) [23] reported that WHtR demonstrated the strongest diagnostic performance among the evaluated anthropometric indices for identifying metabolically healthy obesity, with an optimal cut-off of 0.55 in their study population. However, these findings should not be interpreted as establishing a universal threshold. The performance of WC, WHR, and WHtR may vary according to age, sex, ethnicity, anatomical measurement site, and population characteristics [6,7]. Thus, population-specific validation remains important before adopting specific cut-offs for routine clinical use.

Skinfold Thickness and Anthropometric Prediction Equations

Skinfold thickness provides a low-cost and portable method for estimating body fat, particularly where sophisticated body-composition equipment is unavailable. Kogure et al. (2020) [18] demonstrated acceptable reproducibility but identified systematic differences between skinfold-derived and DXA-derived body-fat estimates.

Anthropometric prediction equations may improve estimation by combining several measurements rather than relying on a single parameter. Castro-Porras et al. (2019) [14] developed an anthropometry-based equation for estimating fat-mass percentage and demonstrated its potential as a practical approach to obesity discrimination. However, prediction equations developed in specific populations should not automatically be generalized to other populations. External validation and standardized measurement procedures are therefore essential before broader clinical implementation.

Neck Circumference

Neck circumference (NC) represents a potentially useful supplementary anthropometric measure because it is rapid, inexpensive, non-invasive, and relatively simple to obtain. Nair et al. (2024) [28] evaluated NC together with BMI, WC, and WHR in 362 female university students and reported its potential usefulness for obesity screening. However, the female-only convenience sample and study-specific characteristics limit generalizability. NC should therefore be considered a complementary screening measure, with further validation required across different sexes, age groups, and populations.

Digital and Three-Dimensional Anthropometry

Digital and 3D anthropometry represent an important development in obesity and body-composition assessment. Tinsley et al. (2020) [15,17] evaluated commercially available 3D optical scanners and demonstrated that these systems can provide rapid anthropometric measurements, although performance differed between devices. Wong et al. (2021, 2023) [19,25] subsequently demonstrated the potential of pose-independent 3D optical imaging for body-composition estimation and evaluated its accuracy across different age, BMI, and ethnic groups. Bennett et al. (2022) [22] also assessed a commercial 3D optical scanner for total and regional body-composition measurements.

Collectively, these studies suggest that 3D technologies can provide rapid and repeatable measurements while potentially reducing some observer-dependent variability. Nevertheless, performance may be affected by device characteristics, body position, scanning conditions, software algorithms, and population characteristics. Consequently, technological feasibility or high group-level agreement should not automatically be interpreted as evidence of individual-level clinical interchangeability.

Smartphone-Based and Emerging Technologies

Smartphone-based anthropometry may improve accessibility by allowing body measurements to be obtained using widely available mobile technology. Nana et al. (2022) [21] evaluated anthropometric and body-composition measurements derived from 2D smartphone images and BIA against criterion methods. McCarthy et al. (2024) [27] investigated a 3D smartphone application for metabolic disease-risk phenotyping, while Florez et al. (2024) [29] evaluated mobile-phone 3D imaging for body-composition estimation against DXA and a four-compartment model.

These technologies offer potential advantages in portability, rapid assessment, automation, and scalability. However, small samples, controlled scanning conditions, image quality, body positioning, software algorithms, and individual-level measurement error remain important limitations. Therefore, larger and more diverse validation studies are required before smartphone-based methods can be considered interchangeable with established criterion methods.

Machine Learning and Artificial Intelligence

Machine-learning approaches provide an opportunity to integrate multiple anthropometric variables and improve body-composition estimation. Harty et al. (2020) [16] demonstrated the application of machine learning with 3D optical imaging for body-fat estimation, while Birk et al. (2025) [30] evaluated machine-learning equations incorporating anthropometric variables in Indian adults [16,30].

Despite this potential, prediction-model evidence requires cautious interpretation. The risk-of-bias assessment showed that three prediction studies were classified as having a low risk of bias and three as having a high risk of bias, with concerns involving participant selection, predictor assessment, and/or statistical analysis. This indicates that strong predictive performance in a development population does not necessarily establish generalizability to other populations or clinical settings. Adequate sample sizes, transparent model development, appropriate statistical analysis, calibration and discrimination assessment, and independent external validation are therefore important before clinical implementation.

Anthropometry, Obesity, Nutrition, and Metabolic Health

The clinical relevance of anthropometry extends beyond identifying elevated body weight. Obesity is a heterogeneous condition in which overall body size, adiposity distribution, and metabolic risk may differ between individuals [1-3]. Guzmán-García et al. (2022) [23] demonstrated the potential of anthropometric indices to distinguish metabolically healthy obesity phenotypes.

Nevertheless, anthropometric measures should not be interpreted as direct measures of insulin resistance, dyslipidaemia, hypertension, or other metabolic disorders. Rather, they provide practical indicators of body size and adiposity that should be interpreted alongside clinical assessment and, when appropriate, biochemical measurements. Anthropometry can also support nutritional and weight-management monitoring, but BMI, WC, and skinfold thickness alone cannot determine dietary adequacy or reliably

distinguish changes in fat mass from changes in lean mass. Therefore, anthropometric assessment should be integrated with dietary assessment, physical activity, clinical evaluation, and appropriate body-composition methods.

Risk of Bias and Certainty of Evidence

Risk-of-bias assessment indicated generally appropriate reporting of participant selection, anthropometric measurement, outcome assessment, and statistical analysis in the eight studies assessed using the structured eight-domain approach. However, Q5 and Q6 were unclear in all eight studies because relevant confounding factors and methods for addressing them were insufficiently reported [15,17,18,21,22,25-27]. Thus, these studies were classified as having some concerns, although this classification does not establish that confounding was actually present. The assessment was based on the Joanna Briggs Institute (JBI) Critical Appraisal Checklist and the information reported in the respective studies [10].

The prediction-model evidence showed greater variability, with three studies classified as having a low risk of bias and three as having a high risk of bias [14,16,19,24,29,30]. The principal concerns involved participant selection, predictor assessment, and statistical analysis [14,16,19,24,29,30]. These findings indicate that prediction-model evidence should be interpreted cautiously, particularly when considering the generalizability of prediction equations and individual-level body-composition estimation.

Similarly, among the five diagnostic-accuracy studies, three were classified as having a high risk of bias and two as having a low risk of bias [20,23,28,31,32]. The principal concerns were related to participant selection and the definition or assessment of the target condition, whereas the index-test and analysis domains were generally rated as low risk [20,23,28,31,32]. These findings indicate that diagnostic-accuracy evidence should be interpreted cautiously, particularly when considering universal diagnostic thresholds and the individual-level application of anthropometric measures.

Clinical Implications

Anthropometry is best used as a multimodal assessment strategy. BMI provides a practical initial measure, while WC and WHtR add information about central adiposity; NC and skinfolds may provide supplementary information when standardized and validated methods are available. Digital and 3D technologies offer potential advantages in rapid, automated, and repeated assessment but should be clinically implemented only after appropriate population-specific validation.

Strengths of the Review

A major strength of this review is its focus on studies that directly evaluated anthropometric validity, reliability, agreement, diagnostic accuracy, and prediction performance, rather than merely reporting anthropometric characteristics. The review also incorporated both established measures and emerging digital, 3D, smartphone, and computational approaches, providing a contemporary assessment of the field.

The choice of anthropometric method should depend on the clinical purpose. A method suitable for population screening may not provide sufficient accuracy for individual body-composition assessment. Therefore, anthropometric findings should be interpreted alongside appropriate reference methods and broader clinical information when precise adiposity assessment is required.

Limitations

The evidence was heterogeneous regarding populations, sample sizes, anthropometric methods, measurement protocols, reference standards, and statistical approaches, preventing meaningful quantitative pooling. Several studies were conducted in specific demographic or geographic populations, limiting generalizability of cut-offs and prediction equations. In addition, some digital-technology studies had small samples, making their findings useful for preliminary validation but insufficient to establish broad clinical applicability.

Future Research

Future studies should use large, multicentre, prospective designs with diverse populations and standardized anthropometric protocols. They should report sensitivity, specificity, AUC, agreement, measurement error, reliability, and appropriate confidence intervals. Prediction equations, machine-learning models, and digital/3D technologies require independent external validation across different populations and devices before routine clinical implementation.

Future research should also determine whether improved anthropometric assessment leads to better obesity management, nutritional care, metabolic-risk stratification, clinical decision-making, and patient outcomes, rather than focusing solely on statistical measurement accuracy.

Overall Interpretation

Overall, the evidence indicates that anthropometry remains a practical, accessible, and clinically valuable component of obesity and body-composition assessment. Conventional measures, including BMI, WC, WHtR, WHR, NC, and skinfold thickness, provide complementary information, while digital, 3D, smartphone-based, and machine-learning approaches offer promising opportunities for more automated and scalable assessment. However, differences in populations, measurement protocols, reference standards, and methodological quality limit the universal application of any single method. Therefore, a standardized, purpose-specific, and multimodal approach, supported by population-specific validation and appropriate reference methods, appears most appropriate for clinical obesity assessment.

Conclusions

This systematic review demonstrates that anthropometric assessment remains a practical, accessible, and clinically useful approach for evaluating obesity, excess adiposity, and body composition. Conventional measures, including BMI, waist circumference, WHtR, WHR, neck circumference, and skinfold thickness, provide complementary information for obesity screening and central-adiposity assessment, while digital, 3D, smartphone-based, and machine-learning approaches show promising potential for more advanced and scalable assessment. However, differences in populations, measurement protocols, reference standards, and methodological quality indicate that no single anthropometric method can currently be considered universally sufficient or interchangeable with criterion body-composition methods. Therefore, a standardized, population-specific, and multimodal approach should be preferred in clinical practice, with the choice of method guided by the intended purpose and required level of accuracy. Further large-scale, multicentre, and externally validated studies are needed to establish standardized thresholds and determine whether emerging digital and predictive technologies can provide reliable individual-level assessment and meaningful improvements in obesity management and clinical decision-making.

Additional Information

Author Contributions

All authors have reviewed the final version to be published and agreed to be accountable for all aspects of the work.

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