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Validity of non-traditional measures of obesity compared to total body fat across the life course: A systematic review and meta-analysis

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Summary

IntroductionTraditional obesity measures including body mass index, waist circumference, waist-to-hip ratio, and waist-to-height ratio have limitations. The primary objective of this study was to identify and review the validity of non-traditional obesity measures, using measures of total body fat as the reference standard, that have been used across multiple life stages. MethodsWe conducted a systematic review and searched MEDLINE, Embase, and PsycINFO. We included observational studies published from 2013 to October 2023 among "the general population" for any life stage that reported the validity of non-traditional obesity measures compared to total body fat reference standards. Separate meta-analyses were performed to pool correlation coefficients and mean differences for non-traditional obesity measures that were evaluated at multiple life stages. ResultsA total of 123 studies were included, and 55 validated non-traditional obesity measures were identified. Of these, 13 were evaluated at multiple life stages. Two-dimensional (2D) digital imaging technologies, three-dimensional (3D) body scanners, relative fat mass (RFM), and mid-upper arm circumference had high or moderate validity (pooled correlation coefficient >0.70). Pooled mean differences were small (<6%) between total body fat percentage from reference standards and from RFM, 2D digital imaging technologies, 3D body scanners, and the body adiposity index. Heterogeneity (I^2) was >75% in most meta-analyses. ConclusionNumerous validated non-traditional obesity measures were identified; relatively few were evaluated at multiple life stages and did not consider health risks associated with adiposity. More research is needed to define valid obesity measures across all life stages that assess health and adiposity.

KEYWORDS
meta-analysis, obesity, systematic review, validation studies

1 | INTRODUCTION

Obesity is a complex chronic disease that is defined by the World Health Organization (WHO) as "abnormal or excessive fat accumulation that presents a risk to health".[1] Global prevalence estimates of obesity across life stages, including children, adolescents, and adults have increased over the past decades.[2,3] Obesity can influence people's capacities for health and abilities for well-being by affecting multiple domains such as cardiovascular, psychological, and musculoskeletal.[4,5] Obesity is an important determinant of health across the life course, and children and adolescents with obesity are more likely to experience obesity in adulthood.[6,7] There is also evidence for intergenerational effects; maternal obesity has been linked to offspring obesity and is a risk factor for both short and long-term maternal and child health issues.[8,9] Thus, early identification of obesity is important for disease management and limiting adverse health consequences during aging through a decline in a person's abilities, capacities, and vitality.[4]

Obesity is most commonly defined in both research and clinical practice as a body mass index (BMI) of 30 kg/m^2 or greater for adults, or a BMI-for-age greater than 2 or 3 standard deviations (or BMI z-score [zBMI]) for children and adolescents.[6] BMI, which is often considered a traditional measure of obesity,[10,11] is easily measured and widely used in general population and clinical settings. In existing work by WHO, commonly used measures of obesity such as BMI have been identified to measure a person's capacity, including vitality.[4] However, BMI does not directly measure body composition or health risks. BMI can incorrectly classify people with higher body weight due to high muscle mass as having obesity.[12,13] BMI can also misclassify people with lower body weight but higher body fat as not having obesity, who are at increased cardiometabolic risk despite a lower BMI.[14,15] Additionally, BMI alone does not indicate the location of body fat such as central obesity, which has been associated with metabolic and cardiovascular disease risk.[16,17] BMI also does not account for differences in adiposity by sex, race/ethnicity, or age.[12] BMI does not consider changes in muscle mass, fat mass, or bone density at different life stages, particularly in older age, and is insufficient to measure changes in body composition that can have an impact on health outcomes across the life course.[4] Emerging research and clinical guidance, including a recent American Medical Association statement, suggest that BMI alone should not be used to define obesity due to these limitations[18]; however, there is no consensus on how obesity should be measured. Other traditional measures include waist circumference (WC), waist-to-hip ratio (WHR), and waist-to-height ratio (WHtR),[10,11] which have many of the same limitations of BMI.

Previous systematic reviews identified several non-traditional anthropometric measures of obesity, defined as anthropometric parameters other than traditionally used measures of BMI, WC, WHR, and WHtR, in children and adults.[10,11] Some examples of the identified non-traditional anthropometric measures were neck circumference, the body adiposity index (BAI), a body shape index (ABSI), and thigh circumference.[10,11] However, these reviews did not identify non-traditional measures beyond anthropometrics. Non-traditional obesity measures could have value, especially those that consider other factors besides weight, account for health risks associated with increased adiposity, and accurately estimate body fat, at all life stages.

The validity of BMI and other traditional measures of obesity including WC, WHR, and WHtR have been evaluated in several previous reviews for multiple life stages.[19–23] However, the validity of non-traditional obesity measures, compared to total body fat measures as the reference standard, across different life stages have not been systematically evaluated. Currently, there is a lack of literature that reviews validated non-traditional measures of obesity, using total body fat as the reference standard and identifies which non-traditional measures have been validated at multiple life stages. The primary objective of our study was to identify and review the validity of non-traditional measures of obesity, using measures of total body fat as the reference standard, that have been used across multiple life stages. The secondary objective was to evaluate differences in the validity by subgroups of the population, including life stages and sex.

2 | METHODS

2.1 | Study design

We conducted a systematic review and meta-analysis. The protocol was prospectively registered in PROSPERO (Registration number: CRD42023474029).

2.2 | Search strategy

We conducted a literature search of MEDLINE (Ovid), Embase (Ovid), and PsycINFO in October 2023. The search strategy consisted of three broad concepts related to obesity measurement (e.g., obesity, anthropometry, body size), body fat (e.g., adiposity, body fat, fat mass), and validity and reliability (e.g., validation study, validity, reliability, reproducibility of results). Appendix S1 presents the full search strategy.

2.3 | Study selection

Search results were imported to Covidence for screening.[24] After the removal of duplicates, unfixed pairs of reviewers (AMP, YYM, MNS, SK, NC, PY, MSV, SG, VD, LNA) independently screened studies first at title and abstract level, and then at the full-text level to determine eligibility based on our inclusion and exclusion criteria. Conflicts were resolved by a third reviewer or by discussion.

We included observational studies (cohort, cross-sectional, case–control) published from 2013 to 2023, written in English, conducted in human participants of any age or life stage who were primarily healthy or part of a "general population", and reported validity of non-traditional obesity measures, compared to measures of total body fat as the reference standard. Non-traditional measures of obesity were defined as measures other than BMI, WC, WHR, and WHtR in isolation, consistent with previous reviews.[10,11] We excluded studies that evaluated traditional measures of BMI, WC, WHR, and WHtR in isolation or measures that we considered reference standards *a priori* including skinfold measurement. We excluded studies focused exclusively on prediction equations generated using machine learning or statistics only.

Eligible total body fat reference standards were determined *a priori* and included dual-energy x-ray absorptiometry (DXA), computed tomography (CT), magnetic resonance imaging (MRI), bioelectrical impedance, air displacement plethysmography (ADP) including the BOD POD and PEA POD, underwater weighing (UWW), isotope dilution such as the deuterium dilution technique, and 3- or 4-component (3C or 4C) models which use a combination of the previously mentioned measures. A cut-point for high total body fat was not defined *a priori* and continuous measures were the primary outcome. Two protocol deviations were implemented due to the high volume of studies in the title and abstract screening phase and to better represent the currently used measures: 1) we narrowed the search time period and limited inclusion to studies published in 2013 to 2023, 2) we excluded skinfold measurement as a reference standard since a large proportion of studies included higher quality reference standards. Skinfold measurement has known limitations such as caliper limits that restrict use and assessment of subcutaneous fat only.[25]

2.4 | Data extraction

Data were extracted from studies that were identified from our search and included in our review after full-text screening. Extraction occurred in two phases, including a study characteristic extraction phase and a validity and reliability extraction phase. The study characteristic extraction phase was completed first by unfixed pairs of independent reviewers (AMP, YYM, MNS, SK, NC, PY, MSV, SG, LNA) in Covidence for all included studies. Conflicts were resolved by AMP, YYM, and LNA. The extracted study characteristics included the following data: year of publication, the country in which the study was published, study design, sample size, the proportion of males, life stage, age range, non-traditional measure(s) of obesity and units (e.g., %, kg, cm) with total body fat mean and standard deviation (SD) if applicable, and reference standard(s) and units (%, kg, or kg/m^2 for fat mass index [FMI]) with total body fat mean and SD. After the study characteristic extraction phase was completed, we evaluated which non-traditional obesity measures were validated at multiple life stages. Life stage categories were determined based on the age ranges of included studies and were broadly defined as: newborns and/or infants/toddlers (≤2 years); children and/or adolescents (3–18 years); and adults (≥18 years). There was overlap between adolescent and adult age ranges because few studies defined adolescence up to 19 years of age or included 17-year-olds with adults. Additionally, children and adolescents needed to be combined since many studies evaluated these life stages together. Single independent reviewers (AMP, YYM, MNS, SK, NC, PY, MSV, SG) then completed the validity and reliability extraction phase (e.g., correlation coefficients, measures of agreement (Kappa and intraclass correlation coefficient [ICC]), sensitivity and specificity, area under the curve (AUC)) only for studies that included the non-traditional obesity measures evaluated at multiple life stages. For studies that had multiple reference standards and/or units, only DXA and percentage units were extracted when possible. This approach was taken because DXA is commonly referred to as the "gold standard" for body composition, it was the most consistently used measure, and to increase homogeneity in methods across studies.

2.5 | Quality assessment

Risk of bias and concerns regarding applicability were assessed using the Quality Assessment of Diagnostic Accuracy Studies (QUADAS-2) tool,[26] only for studies included in the validity and reliability extraction phase. Risk of bias and concerns regarding applicability were assessed for each domain by single independent raters (AMP, YYM, MNS, SK, NC) using high, low, or unclear rating levels. Additional information related to the tool and its modification for this review are included in Appendix S2.

2.6 | Statistical analysis

Separate meta-analyses were performed for each of the following non-traditional obesity measures that were evaluated at multiple life stages and had more than two studies contributing data in at least one of the life stages: the tri-ponderal mass index (TMI), relative fat mass (RFM), the conicity index, neck circumference, mid-upper arm circumference (MUAC), two-dimensional (2D) digital imaging, three-dimensional (3D) body scanners, and the BAI. For each of these non-traditional measures, we calculated the overall pooled estimate, subgroup analyses with estimates pooled by life stage, and when data was available, subgroup analyses with estimates pooled by sex.

For studies that reported the validity of 2D digital imaging applications on both Apple and Samsung mobile devices in the same study sample, we included only estimates from Apple devices in our meta-analysis to avoid duplication and since estimates were similar for both devices. Some studies that reported the validity of the BAI also reported modified versions (pediatric, adjusted, modified, BAI for the Fels Longitudinal Study, BAI with waist circumference), which were not included in our meta-analysis. One study reporting the validity of MUAC evaluated the correlation longitudinally over the first 6 months of life, and only measurement at 3.5 months was added to the meta-analysis. For studies that presented total body fat in various units, only body fat percentage was included in the meta-analysis. All meta-analyses were conducted using the meta package in R version 4.3.2.[27,28] To obtain pooled estimates for each of the previously mentioned eligible non-traditional obesity measures separately, the inverse variance method was applied with the random effects model using the DerSimonian and Laird estimator.[29] For each pooled estimate, the I^2 statistic was used to assess heterogeneity. High heterogeneity was indicated by an I^2 of 75%–100%.[30] Data for meta-analyses were sourced from articles that were included in our review after screening studies identified from our search.

Correlation meta-analyses were performed to generate pooled correlation coefficients and 95% confidence intervals (CI) between each non-traditional obesity measure listed above and total body fat measured from reference standards. Correlation meta-analyses were conducted using the *metacor* function, which automatically applies the Fisher's z-transformation z-values to pool the effects and reconverts the Fisher's z-transformed values back to the original correlation coefficients.[31] Only Pearson's and Spearman's correlation coefficients were applied in the correlation meta-analysis, and unadjusted estimates were selected when available. In cases where studies did not present correlation coefficients, we used the unadjusted R^2 value from simple linear regression, when available, to calculate Pearson's correlation coefficient.

Mean difference meta-analyses were performed using the *meta-cont* function[31] to generate the pooled mean difference and 95% CI between each non-traditional obesity measure that estimated total body fat percentage, including RFM, 2D digital imaging technologies, 3D body scanners, and the BAI, and total body fat percentage from reference standards. Forest plots for mean difference meta-analyses are presented with the experimental mean and SD, which represent the non-traditional obesity measure, and the control mean and SD, which represent the reference standards. If studies did not provide the mean and SD, we calculated them from other statistical measures (e.g., median and range) if possible, or contacted authors.

For both types of meta-analyses, if studies only reported correlation coefficients or means and SDs by subgroups (e.g., sex, age, BMI) rather than overall estimates, each subgroup was added to the meta-analysis separately. For the eight non-traditional measures that were meta-analyzed, a summary table of advantages and disadvantages was created based on discussion among the team.

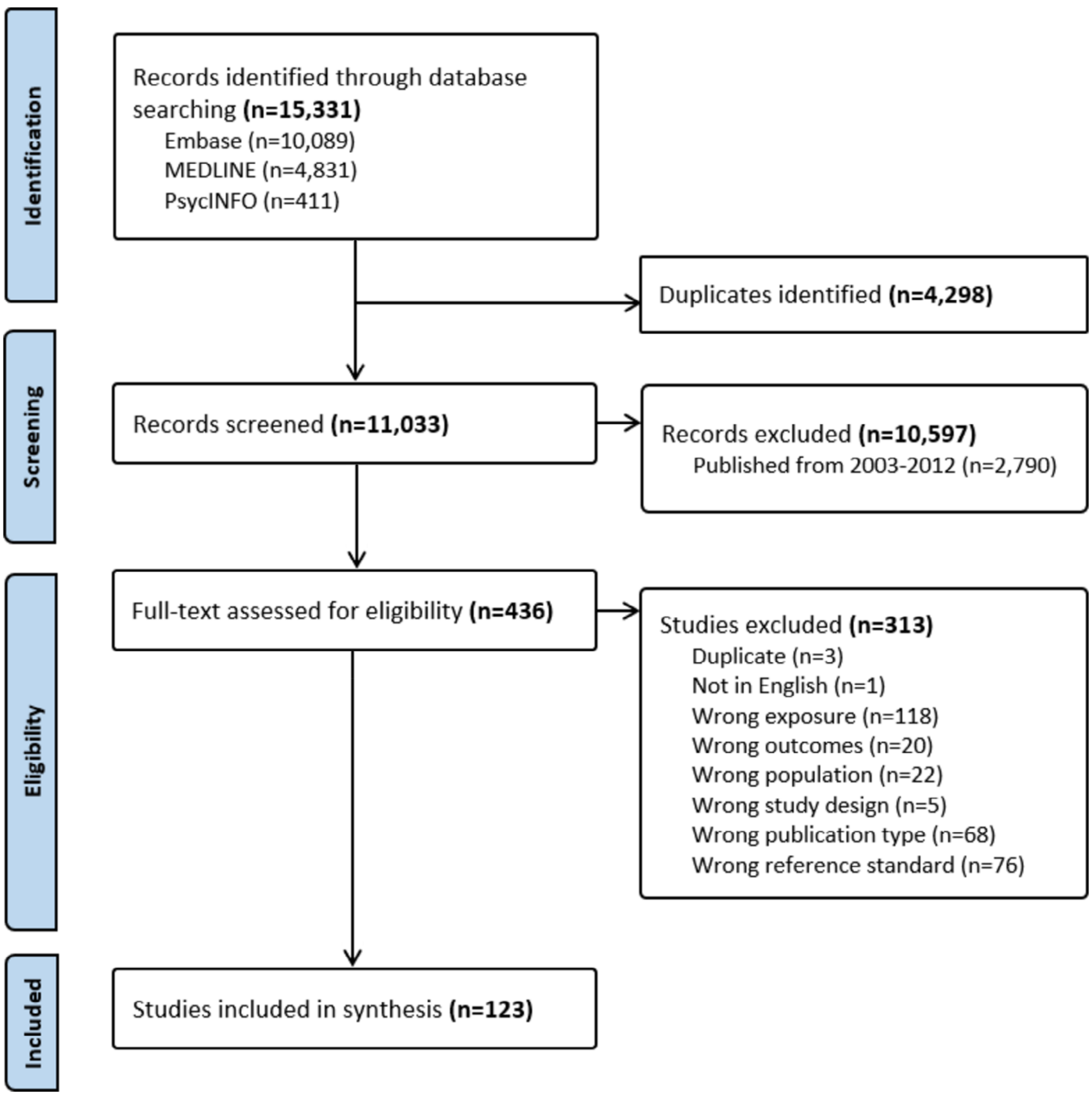

FIGURE 1 PRISMA flow diagram.

2.7 | Sensitivity analyses

Sensitivity analyses were conducted because of heterogeneity in the total body fat reference standard units (i.e., kg, %, kg/m^2). When applicable, sensitivity analyses were conducted by restricting the correlation meta-analyses to studies in which the reference standards were measured in units of total body fat percentage, with other units excluded. For 2D digital imaging technologies, some applications only estimated fat mass in kilograms, and standardized mean difference with Hedge's *g* was calculated to include those studies in meta-analysis.

3 | RESULTS

A total of 15,331 records were identified through database searching from 2003 to October 2023 and 4298 duplicates were removed. In title and abstract screening, 10,597 records were excluded, including 2790 records that were excluded after we limited the year of publication to 2013–2023 only. Full-text screening was conducted for 436 studies, and 123 studies were included in the review (Figure 1).

3.1 | Description of studies

Table 1 provides a summary of the characteristics of included studies and extracted data is provided in Table S1.[32–154] Studies were conducted across North America (30.1%), Asia (25.2%), Europe (19.5%), South America (17.1%), and Africa (5.7%). Five studies (4.1%) included newborns and/or infants/toddlers, 33 studies (26.8%) included children and/or adolescents, and 89 studies (72.4%) included adults. Most studies evaluated validity at one point in time ($n = 121$), had a sample size <500 (59.3%), and included both males and females (89.4%). DXA ($n = 54$; 43.9%) and bioelectrical impedance ($n = 49$; 39.8%) were the most common reference standards for total body fat. Tables S2 and S3 demonstrate the number of studies for each non-traditional obesity measure by the reference standard(s) for total body fat when determining validity. For each reference standard, the most common unit was total body fat percentage.

3.2 | Validated non-traditional obesity measures

Overall, 55 validated non-traditional obesity measures were identified, which are briefly described in Table 2. Most of the validated non-traditional obesity measures were focused on body size only and did not comprehensively measure health risks. Of the 55 validated non-traditional obesity measures, 13 were evaluated at multiple life stages across 104 studies. These 13 measures included the TMI, the BAI, RFM, the conicity index, the body roundness index (BRI), MUAC, neck circumference, waist-to-thigh ratio, thigh circumference, 3D body scanners, 2D digital imaging technologies, near-infrared reactance/reflectance (NIR), and pictorial body silhouettes (Table 2). Few studies

TABLE 1 Characteristics of included studies reporting the validity of non-traditional obesity measures, compared to a body fat reference standard ($n = 123$).

Characteristic	*n* (%)
Continent	
North America	37 (30.1%)
Asia	31 (25.2%)
Europe	24 (19.5%)
South America	21 (17.1%)
Africa	7 (5.7%)
Countries within Multiple Continents (Australia, Brazil, Canada, China, Colombia, Finland, India, Kenya, Portugal, South Africa, UK, USA)	1 (0.8%)
Unclear	2 (1.6%)
Year of Publication	
2013–2016	41 (33.3%)
2017–2020	48 (39.0%)
2021–2023	34 (27.6%)
Sex	
Male only	4 (3.3%)
Female only	9 (7.3%)
Both male and female	110 (89.4%)
Sample Size	
< 100	22 (17.9%)
100–499	51 (41.5%)
500–999	17 (13.8%)
1000-9999	27 (22.0%)
≥ 10,000	6 (4.9%)
Life Stage [a]	
Newborns and/or Infants/Toddlers (≤2 years) [b]	5 (4.1%)
Children and/or Adolescents (3–18 years) [c]	33 (26.8%)
Adults (≥18 years) [d]	89 (72.4%)
Longitudinal Measures of Validity	
Yes	2 (1.6%)
No	121 (98.4%)
Reference Standard [e]	
Dual energy x-ray absorptiometry (DXA)	54 (43.9%)
Bioelectrical Impedance	49 (39.8%)
Air Displacement Plethysmography (ADP; BOD POD/PEA POD)	17 (13.8%)
3-component (3C) or 4-component (4C) models	8 (6.5%)
Isotope dilution	2 (1.6%)
Underwater weighing (UWW)	1 (0.8%)
Computed Tomography (CT)	0 (0%)
Magnetic Resonance Imaging (MRI)	0 (0%)

[a]Percentages do not sum to 100% and *n* do not sum to 123 because some studies evaluated multiple life stages.
[b]In one study, non-traditional measures were obtained in utero to predict newborn adiposity.
[c]Five studies included 19-year-olds in the study sample.
[d]Two studies included 17-year-olds in the study sample.
[e]Percentages do not sum to 100% and *n* do not sum to 123 because some studies had multiple reference standards.

TABLE 2 Brief description of each non-traditional obesity measure identified, with the number of studies for each overall and by life stage group ($n = 123$).

Non-traditional obesity measure	Units	Brief description/equation	Overall number of studies [a]	Number of studies among newborns and/or infants/ toddlers (≤2 years) [b]	Number of studies among children and/or adolescents (3–18 years) [b]	Number of studies among adults (≥18 years) [b]
Tri-ponderal mass index (TMI)	kg/m^3	TMI = weight (kg)/height $(m)^3$	10	2	6	2
Tri-ponderal mass index (TMI) standard deviation score (SDS)	NA	Calculated using age- and sex-specific least mean square reference values.	1	none	1	none
A body shape index (ABSI)	$m^{11/6} \times kg^{-2/3}$	ABSI = waist circumference (m)/(BMI $(kg/m^2)^{2/3}$ × height $(m)^{1/2}$	4	none	none	4
A body shape index z-score (zABSI)	NR	zABSI = (ABSI – $ABSI_{mean}$)/$ABSI_{SD}$ Mean and SD are age- and sex-specific	1	none	none	1
Body adiposity index (BAI)	Estimates body fat percentage (%)	BAI = (hip circumference (cm)/(height $(m)^{1.5}$) – 18	43	none	11	34
Pediatric body adiposity index (BAIp)	Estimates body fat percentage (%)	BAIp = (hip circumference (cm)/(height $(m)^{0.8}$) – 38	3	none	3	none
Body adiposity index for the Fels Longitudinal Study (BAIFels)	Estimates body fat percentage (%)	BAIFels = [1.26 × (hip circumference (cm)/(height $(m)^{1.4}$)) – 32.85]	4	none	none	4
Adjusted body adiposity index (BAIadj)	Estimates body fat percentage (%)	BAIadj = (hip circumference (cm)/ (stature (m) × √stature (m))) – 17.3	1	none	1	none
Modified body adiposity index (MBAI)	Estimates body fat percentage (%)	MBAI = 23.6 + 0.5 × BAI% Add 2.2 if BMI ≥ 50 kg/m^2 and 2.4 if WHR ≥ 1.05	1	none	none	1
Body adiposity index with waist circumference (BAIw)	Estimates body fat percentage (%)	BAIw = (waist circumference/height$^{1.5}$) – 18	1	none	1	none
Relative fat mass (RFM)	Estimates body fat percentage (%)	RFM = 64 – (20 × (height (m)/waist circumference (m))) + (12 × sex) Sex equals 0 for males and 1 for females	10	none	3	7
Pediatric relative fat mass (RFMp)	Estimates body fat percentage (%)	RFMp = 74 – (22 × [height/waist circumference]) + (5 × sex) Sex equals 0 for males and 1 for females	2	none	2	none
Clínica Universidad de Navarra-Body Adiposity Estimator (CUN-BAE)	Estimates body fat percentage (%)	BF % = −44.988 + (0.503 × age) + (10.689 × sex) + (3.172 × BMI) – (0.026 × BMI^2) + (0.181 × BMI × sex) – (0.02 × BMI × age) – (0.005 × BMI^2 × sex) + (0.00021 × BMI^2 × age) Where male = 0 and female = 1 for sex, and age is in years	3	none	none	3
Conicity index	NA	Conicity index = waist circumference (m)/(0.109 × (√weight (kg)/height (m)))	6	none	3	3
Body roundness index (BRI)	NA	BRI = 364.2–365.5 × (√(1 – ((waist circumference (m)/(2π))^2/ (height (m)/2)^2)))	2	none	1	1

TABLE 2 (Continued)

Non-traditional obesity measure	Units	Brief description/equation	Overall number of studies [a]	Number of studies among newborns and/or infants/toddlers (≤2 years) [b]	Number of studies among children and/or adolescents (3–18 years) [b]	Number of studies among adults (≥18 years) [b]
Hip index (HI)	NA	$HI = \text{hip circumference (cm)} \times (\text{height}/\text{height}_{average})^{0.310} \times (\text{weight}/\text{weight}_{average})^{0.48215}$	1	none	none	1
Hip index z-score (zHI)	NA	$zHI = (HI - HI_{mean})/HI_{SD}$ Mean and SD are age- and sex-specific	1	none	none	1
Body fat index (BFI)	Estimates body fat percentage (%)	$BFI = -28.294 + (3.740 \times \text{race}) - (0.074 \times \text{age}) + (11.303 \times \text{sex}) - (0.169 \times \text{stature (cm)}) + (0.079 \times \text{weight (kg)}) + (0.671 \times \text{waist circumference (cm)})$ Where 0 = Asian and 2 = non-Asian for race Age in years Where 1 = boys and 2 = girls for sex	1	none	1	none
Weight-adjusted waist index (WWI)	cm/√kg	$WWI = \text{waist circumference (cm)}/(\sqrt{\text{weight (kg)}})$	1	none	none	1
Anthropometric risk index (ARI)	NA	Calculated as the product of the logarithmic odds ratio from separate non-linear regression for height, BMI, ABSI, and HI.	1	none	none	1
Arm muscle area (AMA)	mm^2	$AMA = 1/(4\pi) \times (\text{MUAC} - \pi \times \text{triceps skinfold})^2$	1	none	1	none
Arm fat area (AFA)	cm^2	$AFA = (\text{MUAC (cm)})^2/4\pi) - [(\text{MUAC (cm)} - (\pi \times \text{triceps skinfold (cm)}))^2/4\pi]$	1	none	1	none
DoD circumference equation	Estimates body fat percentage (%)	Women: $\%BF = [163.205 \log10 (\text{waist} + \text{hip} - \text{neck})] - [97.684 \log10(\text{height})] - 78.38$ Men: $\%BF = [86.010 \log10 (\text{abdomen} - \text{neck})] - [70.041 \log10(\text{height})] - 36.76$ Where height and circumference measures are in inches	1	none	none	1
Waist corrected BMI (wBMI)	kg/m	$wBMI = \text{weight} \times \text{waist circumference}/\text{height}^2 = \text{waist circumference (m)} \times \text{BMI (kg/m}^2)$	1	none	none	1
Normalized weight adjusted index (NWAI)	NA	$NWAI = [(\text{weight (kg)}/10) - (10 \times \text{height (m)}) + 10]$	1	none	none	1
Visceral adiposity index (VAI)	NA	Male: $[\text{waist circumference}/39.68 + (1.88 \times \text{BMI})] \times \text{triglycerides}/1.03) \times (1.31/\text{high density lipoproteins})$ Female: $[\text{waist circumference}/36.58 + (1.89 \times \text{BMI})] \times \text{triglycerides}/0.81) \times (1.52/\text{high density lipoproteins})$	1	none	none	1
Abdominal volume index (AVI)	NA	$AVI = [2\ (\text{waist circumference})^2 + 0.7\ (\text{waist circumference}/\text{hip circumference})^2]/1000$	1	none	none	1
Waist hip index (WHI)	NA	$WHI = \text{waist circumference (cm)} + \text{hip circumference (cm)}$	1	none	none	1
Height weight difference index (HWDI)	NA	$HWDI = \text{height (cm)} - \text{weight (kg)}$	1	none	none	1

(Continues)

TABLE 2 (Continued)

Non-traditional obesity measure	Units	Brief description/equation	Overall number of studies [a]	Number of studies among newborns and/or infants/ toddlers (≤2 years) [b]	Number of studies among children and/or adolescents (3–18 years) [b]	Number of studies among adults (≥18 years) [b]
Anthropometric empirical indicator (AEI)	kg/m^2	AEI = BMI × abdomen circumference/ hip circumference × chest circumference/neck circumference	2	none	none	2
The Hume's equation	kg	Lean body mass (LBM) men (kg) = (0.32818 × weight) + (0.33929 × height) – 29.5336 LBM women (kg) = (0.29569 × weight) + (0.41813 × height) – 43.2933 FM (kg) = weight – LBM Weight is expressed in kg and height in cm for both equations	1	none	none	1
Mid-upper arm circumference (MUAC)	cm	Typically measured midway between the acromion and the olecranon processes, with the arm hanging loosely at the side of the body, using a measuring tape.	10	3	7	2
Mid-upper arm circumference (MUAC) for age z-score	NA	NA	1	none	1	none
Neck circumference	cm	Typically measured just below the laryngeal prominence using a measuring tape. [c]	8	none	3	5
Waist-to-weight ratio	cm/√kg	Waist-to-weight ratio = waist circumference (cm)/(weight (kg) × 0.5)	1	none	1	none
Waist-to-thigh ratio	NA	Waist-to-thigh ratio = waist circumference/thigh circumference	2	none	1	1
Thigh-to-height ratio (THtR)	NA	THtR = thigh circumference (cm)/height (cm)	2	none	none	2
Thigh-to-hip ratio (THpR)	NA	THpR = thigh circumference (cm)/hip circumference (cm)	1	none	none	1
Waist + hip to height ratio	NA	(waist circumference + hip circumference)/height	2	none	none	2
Wrist circumference	cm	Typically measured at the most prominent aspect of the radial styloid process using a measuring tape.	1	none	1	none
Thigh circumference	cm	Typically measured using a measuring tape.	3	1	none	2
Hip-to-height ratio	NA	hip circumference/height	2	none	none	2
Chest circumference	cm	Typically measured using a measuring tape.	1	none	none	1
3D body scanners (e.g., optical [3DO], photonic)	Most estimate body fat mass (kg), percentage (%), and/or fat mass index (FMI; kg/m^2) [d]	The participant stands on a rotating platform as stationary sensors and/or cameras scan the whole body. Surface areas, volumes, and/or shape are extracted by the device to estimate body composition.	13	none	2	12
2D digital imaging technology (e.g., applications)	Estimates body fat mass (kg) and/or percentage (%)	2D digital images of a participant's whole body are captured using a smartphone device (e.g., iPhone, iPad, Samsung Galaxy) or other digital camera, and processed to estimate body fat.	10	none	1	10

TABLE 2 (Continued)

Non-traditional obesity measure	Units	Brief description/equation	Overall number of studies [a]	Number of studies among newborns and/or infants/toddlers (≤2 years) [b]	Number of studies among children and/or adolescents (3–18 years) [b]	Number of studies among adults (≥18 years) [b]
Near infrared reactance/reflectance (NIR)	Estimates fat mass (g) for infant study; estimates body fat percentage for adult study	Infants: NIR device is placed at subscapular and flank sites and wavelengths are collected. Weight and length are also considered. Adults: NIR device is placed at the mid-point on the belly of the dominant arm biceps muscle. Infrared scans over a range of wavelengths are performed and averaged. Sex, weight, and height, and age are also entered into the device.	2	1	none	1
Lower facial geometry parameter	NA	Facial photographs are collected using a gray background and processed for size and percentage of head coverage to characterize facial geometry.	1	none	none	1
Portable ultrasound-based device	Estimates body fat mass (kg) and percentage (%)	Involves measures of subcutaneous fat thickness in the abdominal and mid-thigh area and includes weight and waist circumference.	1	none	none	1
Dahlmann body analysis (DBA)	Estimates body fat percentage (%)	Unclear; anthropometric model that includes abdomen circumference.	1	none	none	1
Edmonton Obesity Staging System (EOSS)	NA	A four-stage system that is based on the presence of comorbidities, functional limitations, and mental health decline and used as a composite indicator to define obesity.	1	none	none	1
Fetal abdominal subcutaneous tissue (FAST)	mm	Ultrasound is used to measure the anterior abdominal wall anterior to the margins of the ribs, using magnification at the same level as the abdominal circumference proximal to the cord insertion.	1	1	none	none
Fetal thigh fat	g/mm	Ultrasound is used to calculate the distance from the outer border of the femur to the outer border of the subcutaneous layer. Then, the thigh muscle value is subtracted. Thigh muscle is the distance from the outer border of the mid-femur to the inner edge of the subcutaneous layer.	1	1	none	none
Total and regional volumes from 3D stereovision body imaging (SBI)	Estimates volume (L)	3D stereovision body imaging measures the body size and shape of participants. Regional volumes derived included torso, thigh, abdomen-hip, and ratios of these measures (torso to total body, abdomen-hip to total body; abdomen-hip to torso; thigh to total body; thigh to torso; thigh to abdomen-hip).	1	none	none	1
Pictorial body silhouettes	NA	Participants select their body silhouette from 8 or 9 items ranging from very lean to severe obesity.	4	none	2	2

(Continues)

TABLE 2 (Continued)

Non-traditional obesity measure	Units	Brief description/equation	Overall number of studies [a]	Number of studies among newborns and/or infants/toddlers (≤2 years) [b]	Number of studies among children and/or adolescents (3–18 years) [b]	Number of studies among adults (≥18 years) [b]
BMI adjusted for fat mass (BMIfat)	NA	BMIfat = [(3 × weight (kg) + 4 × fat mass (%))/height (m)]	2	none	none	2

[a]The overall number of studies does not sum up to 123 because some studies evaluated multiple non-traditional obesity measures.
[b]The number of studies across the life stages for each non-traditional measure does not sum to the number of studies overall for each non-traditional measure or 123 because some studies evaluated multiple life stages.
[c]One study obtained neck circumference from a 3D photonic scanner.
[d]One study estimated areal surface roughness.

evaluated the reliability of measures, and no studies assessed the reliability longitudinally across the life stages (Table S1).

3.3 | Meta-analyses for the validity of the non-traditional obesity measures evaluated at multiple life stages

There were eight non-traditional obesity measures included in the correlation meta-analyses and four of these were also included in the mean difference meta-analyses, as described in the Methods. Summaries of the pooled correlation coefficients and pooled mean differences with I^2 are provided in Figures 2 and 3, respectively, with the full meta-analyses' forest plots included in Figures S1–S12.

3.3.1 | Tri-ponderal mass index (TMI)

There were 11 studies that evaluated the validity of the TMI ($n = 10$) or the age- and sex-specific TMI standard deviation score (SDS) ($n = 1$) and 6 were included in the meta-analysis ($n = 16{,}577$), as 5 studies did not provide correlation coefficients.[35,69,116,142,149] The pooled analysis showed a moderate correlation between the TMI and total body fat measured from reference standards ($r = 0.69$; 95% CI: 0.48–0.82; $I^2 = 99\%$). There was a statistically significant difference between life stage subgroups ($p = 0.04$), with a higher pooled correlation coefficient among children and adolescents ($r = 0.74$; 95% CI: 0.53–0.86; $n = 16{,}298$; 4 studies; $I^2 = 99\%$) than newborns ($r = 0.51$; 95% CI: 0.42–0.59; $n = 279$; 2 studies; $I^2 = 0\%$) (Figure 2, Figure S1).

3.3.2 | Relative fat mass (RFM)

There were 10 studies that evaluated the validity of RFM ($n = 10$) or pediatric RFM (RFMp) ($n = 2$). Seven studies were pooled for the correlation meta-analysis ($n = 20{,}230$) and 9 studies for the mean difference meta-analysis ($n = 33{,}687$). For the correlation meta-analysis, 3 studies were excluded since they did not provide correlation coefficients,[110,141,142] and one study was excluded from the mean difference meta-analysis as the mean and SD were not available.[142] There was a moderate correlation between RFM and total body fat percentage measured from reference standards ($r = 0.77$; 95% CI: 0.72–0.81; $I^2 = 97\%$) for the overall pooled analysis, and this was consistent with subgroups of children and adolescents ($r = 0.78$; 95% CI: 0.60–0.88; $n = 1051$; 2 studies; $I^2 = 96\%$) and adults ($r = 0.74$; 95% CI: 0.70–0.78; $n = 19{,}179$; five studies; $I^2 = 94\%$). There was no statistically significant difference between life stage subgroups ($p = 0.66$) (Figure 2, Figure S2). There was no evidence of a difference in means between total body fat percentage estimated from RFM and observed from reference standards (MD = -0.04%; 95% CI: −0.93–0.85; $I^2 = 96\%$). We found a statistically significant difference between life stage subgroups ($p = 0.02$), suggesting for adults, RFM overestimated total body fat percentage by a mean difference of 0.76% (95% CI: −0.25–1.77; 7 studies, $n = 32{,}636$; $I^2 = 96\%$), while for children and adolescents, RFM underestimated total body fat percentage by a mean difference of −1.57% (95% CI: −3.29–0.14; 2 studies, $n = 1051$; $I^2 = 87\%$) (Figure 3, Figure S3).

3.3.3 | Conicity index

There were six studies that evaluated the validity of the conicity index, and five were included in the meta-analysis ($n = 3052$) since one study did not provide a correlation coefficient.[102] The overall pooled analysis indicated a low correlation between the conicity index and total body fat percentage measured from reference standards ($r = 0.44$; 95% CI: 0.32–0.55; $I^2 = 93\%$). This was consistent for life stage subgroups of adults ($r = 0.49$; 95% CI: 0.31–0.64; $n = 1952$; 3 studies; $I^2 = 95\%$) and children and adolescents ($r = 0.38$; 95% CI: 0.24–0.51; $n = 1100$; 2 studies; $I^2 = 86\%$), and there was no evidence of a statistically significant difference between life stage subgroups ($p = 0.31$) (Figure 2, Figure S4).

Non-traditional measure	Life stage subgroup or overall	Pooled correlation coefficient (95% CI)	Forest plot of pooled correlation coefficients with 95% CI	Number of studies	Total n	Heterogeneity: I^2	Test for subgroup differences: p-value
2D digital imaging technologies	Children/Adolescents	NA		1	97	NA	NA
	Adults	0.91 (0.87–0.94)		7	1230	92%	
	Overall	0.90 (0.86–0.93)		7	1327	92%	
3D body scanners	Children, Adolescents, Adults, combined	NA		1	77	NA	NA
	Adults	0.89 (0.77–0.94)		5	789	96%	
	Overall	0.88 (0.78–0.94)		6	866	95%	
Mid-upper arm circumference (MUAC)	Newborns/Infants/Toddlers	0.68 (0.57–0.77)		3	605	68%	0.48
	Children/Adolescents	0.74 (0.63–0.82)		5	8245	98%	
	Adults	NA		1	58	NA	
	Overall	0.71 (0.62–0.79)		9	8908	98%	
Neck circumference	Children/Adolescents	0.60 (0.42–0.74)		2	170	60%	0.22
	Adults	0.48 (0.38–0.57)		5	2523	84%	
	Overall	0.52 (0.43–0.59)		7	2693	83%	
Relative fat mass (RFM)	Children/Adolescents	0.78 (0.60–0.88)		2	1051	96%	0.66
	Adults	0.74 (0.70–0.78)		5	19,179	94%	
	Overall	0.77 (0.72–0.81)		7	20,230	97%	
Tri-ponderal mass index (TMI)	Newborns	0.51 (0.42–0.59)		2	279	0%	0.04
	Children/Adolescents	0.74 (0.53–0.86)		4	16,289	99%	
	Overall	0.69 (0.48–0.82)		6	16,577	99%	
Body adiposity index (BAI)	Children/Adolescents	0.53 (0.46–0.60)		9	20,444	96%	<0.01
	Adults	0.68 (0.65–0.72)		31	29,197	96%	
	Overall	0.63 (0.59–0.66)		39	49,641	96%	
Conicity index	Children/Adolescents	0.38 (0.24–0.51)		2	1100	86%	0.31
	Adults	0.49 (0.31–0.64)		3	1952	95%	
	Overall	0.44 (0.32–0.55)		5	3052	93%	
			0.0 0.2 0.4 0.6 0.8 1.0 Correlation Coefficient				

FIGURE 2 Summary of *pooled correlation coefficients* for each non-traditional obesity measure that was evaluated at more than one life stage, compared to total body fat measured from a reference standard, overall, and by life stage subgroup. Data is not presented for subgroups with only 1 study.

Non-traditional measure	Life stage subgroup or overall	Pooled mean difference (95% CI)	Forest plot of pooled mean differences with 95% CI	Number of studies	Total n	Heterogeneity: I^2	Test for subgroup differences: p-value
2D digital imaging technologies	Children/Adolescents	NA		1	97	NA	NA
	Adults	-0.64 (-1.33–0.06)		7	1986	44%	
	Overall	-0.59 (-1.24–0.05)		7	2083	37%	
3D body scanners	Children/Adolescents	NA		1	112	NA	NA
	Children, Adolescents, Adults, combined	NA		1	77	NA	
	Adults	-0.58 (-1.91–0.74)		6	1616	84%	
	Overall	-0.60 (-1.76–0.56)		8	1805	81%	
Relative fat mass (RFM)	Children/Adolescents	-1.57 (-3.29–0.14)		2	1051	87%	0.02
	Adults	0.76 (-0.25–1.77)		7	32,636	96%	
	Overall	-0.04 (-0.93–0.85)		9	33,687	96%	
Body adiposity index (BAI)	Children/Adolescents	5.11 (1.57–8.65)		7	5353	100%	<0.01
	Adults	-0.44 (-2.23–1.36)		29	27,514	100%	
	Overall	0.61 (-1.51–2.73)		35	32,867	100%	
			-4.0 -2.0 0.0 2.0 4.0 6.0 8.0 10.0 Mean Difference				

FIGURE 3 Summary of *pooled mean differences* for each non-traditional obesity measure that was evaluated at more than one life stage, compared to total body fat percentage measured from a reference standard, overall, and by life stage subgroup. Data is not presented for subgroups with only 1 study.

3.3.4 | Neck circumference

There were eight studies that assessed the validity of neck circumference. One study was excluded from the meta-analysis as a correlation coefficient was not reported.[43] The overall pooed analysis indicated a low correlation between neck circumference and total body fat measured from reference standards ($r = 0.52$; 95% CI: 0.43–0.59; $n = 2693$; seven studies; $I^2 = 83\%$). Among adults, there was also a low correlation ($r = 0.48$; 95% CI: 0.38–0.57; $n = 2523$; five studies; $I^2 = 84\%$). Among children and adolescents, there was a moderate correlation between neck circumference and total body fat ($r = 0.60$; 95% CI: 0.42–0.74; $n = 170$; two studies; $I^2 = 60\%$) (Figure 2, Figure S5). However, there was no evidence of a statistically significant difference between life-stage subgroups ($p = 0.22$).

3.3.5 | Mid-upper arm circumference (MUAC)

There were 10 studies that evaluated the validity of MUAC, of which 9 studies were included in the pooled analysis ($n = 8908$) since one study was excluded as correlation coefficients were not reported.[106] Overall, the pooled correlation coefficient was 0.71 (95% CI: 0.62–0.79; $I^2 = 98\%$), which was consistent by life stage subgroups, including newborns and infants/toddlers ($r = 0.68$; 95% CI: 0.57–0.77; $n = 605$; three studies; $I^2 = 68\%$) and children and adolescents ($r = 0.74$; 95% CI: 0.63–0.82; $n = 8245$; five studies; $I^2 = 98\%$). Only one study included in the meta-analysis was among adults. There was no statistically significant difference between life stage subgroups ($p = 0.48$) (Figure 2, Figure S6).

3.3.6 | 2D digital imaging technologies

There were 10 studies that evaluated the validity of various 2D digital imaging technologies. Three studies were excluded from the correlation meta-analysis since correlation coefficients were not reported.[65,92,105] Overall, the pooled analysis demonstrated a high correlation between 2D digital imaging technologies and total body fat measured from reference standards ($r = 0.90$; 95% CI: 0.86–0.93; $n = 1327$; 7 studies; $I^2 = 92\%$). Among adults, there was also a high correlation ($r = 0.91$; 95% CI = 0.87–0.94; $n = 1230$; seven studies; $I^2 = 92\%$) (Figure 2, Figure S7). For the mean difference meta-analysis, a total of seven studies were included in the pooled analysis ($n = 2083$), and three studies were excluded as these studies did not report mean and SD[107] or the 2D digital imaging technologies only estimated total body fat mass.[64,65] There was no evidence of a difference in means between total body fat percentage estimated from various 2D digital imaging technologies and observed from reference standards (MD = -0.59%; 95% CI: −1.24–0.05; $I^2 = 37\%$). This finding was consistent among adults (MD = -0.64%; 95% CI: −1.33–0.06; $n = 1986$; seven studies; $I^2 = 44\%$) (Figure 3, Figure S8). In both meta-analyses, only one study evaluated the validity of a 2D digital imaging technology among children and adolescents.

3.3.7 | 3D body scanners

There were 13 studies that evaluated the validity of various 3D body scanners. We included six studies in the correlation meta-analysis ($n = 866$), as seven studies did not report correlation coefficients.[38,108,109,124,131,139,140] The pooled analysis showed a high correlation between 3D body scanners and total body fat percentage measured from reference standards ($r = 0.88$; 95% CI: 0.78–0.94; $I^2 = 95\%$). The pooled correlation coefficient among adults also indicated a high correlation ($r = 0.89$; 95% CI: 0.77–0.94; $n = 789$; five studies; $I^2 = 96\%$). (Figure 2, Figure S9). Eight studies were included in the mean difference meta-analysis ($n = 1805$), as five studies did not provide means and SDs.[95,107,108,124,131] The pooled mean difference between total body fat percentage estimated from 3D body scanners and observed from reference standards was −0.60% (95% CI: −1.76–0.56; $I^2 = 81\%$), and there was no evidence of a difference in means. For adults, the pooled mean difference was −0.58% (95% CI: −1.91–0.74; $n = 1616$; six studies; $I^2 = 84\%$) (Figure 3, Figure S10). In the mean difference meta-analysis, one study was conducted among children and adolescents, and in both meta-analyses, one study was conducted among children, adolescents, and adults combined.

3.3.8 | Body adiposity index (BAI)

There were 43 studies that evaluated the validity of the BAI. For the correlation meta-analysis, three studies were excluded due to not reporting correlation coefficients.[52,102,121] For two studies that used the same reference standard, study sample, and evaluated the BAI, we included the most recent study in the meta-analysis only.[66] Overall, the pooled analysis demonstrated a moderate correlation ($r = 0.63$; 95% CI: 0.59–0.66; $n = 49{,}641$; 39 studies; $I^2 = 96\%$). There was a statistically significant difference between life stage subgroups ($p < 0.01$). The pooled correlation coefficient was lower among children and adolescents ($r = 0.53$; 95% CI: 0.46–0.60; $n = 20{,}444$; 9 studies; $I^2 = 96\%$) and higher among adults ($r = 0.68$; 95% CI: 0.65–0.72; $n = 29{,}197$; 31 studies; $I^2 = 96\%$) (Figure 2, Figure S11). For the mean difference meta-analysis, 8 studies were excluded since they either did not provide mean and SD, the reference standard was not measured as total body fat percentage, or studied the same sample as mentioned above.[55,58,66,89,96,102,144,147] There was no evidence of a difference in means between total body fat percentage estimated from the BAI and observed from reference standards (MD = 0.61%; 95% CI: −1.51–2.73; $n = 32{,}867$; 35 studies; $I^2 = 100\%$). There was a statistically significant difference between life stage subgroups ($p < 0.01$). For adults, there was no evidence of a difference in means (MD = -0.44%; 95% CI: −2.23–1.36; $n = 27{,}514$; 29 studies; $I^2 = 100\%$). However, for children and adolescents, the BAI overestimated the participants total body fat percentage by 5.11% (95% CI: 1.57–8.65; $n = 5353$; seven studies; $I^2 = 100\%$) (Figure 3, Figure S12).

3.3.9 | Sex subgroup analyses

The summaries from the sex subgroup meta-analyses of pooled correlation coefficients and pooled mean differences are provided in Figures 4 and 5, respectively, with the full meta-analyses' plots included in Figures S13–S23. Among the correlation coefficient meta-analyses for the TMI, RFM, conicity index, neck circumference, MUAC, 2D digital imaging technologies, and the BAI, there were no statistically significant differences between males and females. Correlation coefficient meta-analysis was not performed for 3D body scanners as there were no studies contributing data. The mean difference meta-analyses for RFM, 2D digital imaging technologies, and 3D body scanners also demonstrated no statistically significant difference between males and females ($p > 0.05$) (Figure 3, Figures S13–S22). However, for the BAI, there was evidence of a statistically significant difference between males and females ($p < 0.01$). For females, the BAI underestimated the total body fat percentage (MD = -2.20%; 95% CI: −4.15– −0.25; n = 21,041; 29 studies). For males, the BAI overestimated total body fat percentage (MD = 2.55%; 95% CI: −0.00–5.11; n = 10,317; 28 studies) (Figure S23).

3.3.10 | Sensitivity analyses

The sensitivity analyses restricted to studies that reported total body fat percentage for the reference standards demonstrated similar pooled correlation coefficients to the primary analyses (Figures S24–S30). Sensitivity analyses were not conducted for RFM, the conicity index, or 3D body scanners in overall, life stage subgroup, and sex subgroup analyses. This was based on all reference standards being reported in percentage units across studies included in the meta-analyses. For sex subgroup analyses, sensitivity analyses were

Non-traditional measure	Sex subgroup	Pooled correlation coefficient (95% CI)	Forest plot of pooled correlation coefficients with 95% CI	Number of studies	Total n	Heterogeneity: I²	Test for subgroup differences: p-value
2D digital imaging technologies	Female	0.89 (0.74–0.96)		4	457	96%	0.67
	Male	0.91 (0.84–0.96)		4	305	89%	
Mid-upper arm circumference (MUAC)	Female	0.73 (0.46–0.87)		4	4,232	97%	0.91
	Male	0.75 (0.34–0.92)		3	3,671	98%	
Neck circumference	Female	0.49 (0.31–0.63)		5	771	79%	0.59
	Male	0.57 (0.29–0.76)		3	638	87%	
Relative fat mass (RFM)	Female	0.73 (0.64–0.80)		6	11,296	89%	0.61
	Male	0.76 (0.69–0.81)		7	8,934	90%	
Tri-ponderal mass index (TMI)	Female	0.60 (0.46–0.71)		2	348	68%	0.32
	Male	0.52 (0.44–0.59)		2	383	0%	
Body adiposity index (BAI)	Female	0.64 (0.60–0.68)		29	21,154	94%	0.07
	Male	0.59 (0.53–0.63)		27	10,006	92%	
Conicity index	Female	0.34 (0.21–0.45)		4	1,734	86%	0.10
	Male	0.53 (0.33–0.68)		4	1,231	94%	

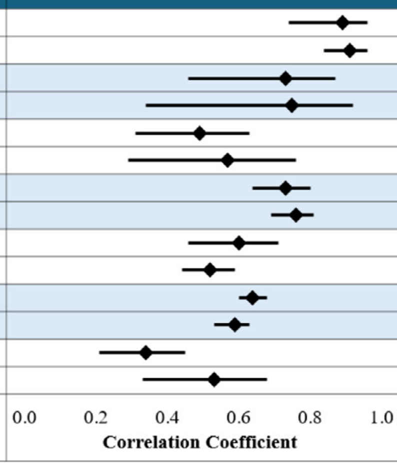

FIGURE 4 Summary of *pooled correlation coefficients* for each non-traditional obesity measure that was evaluated at more than one life stage, compared to total body fat measured from a reference standard, by sex subgroup.

Non-traditional measure	Sex subgroup	Pooled mean difference (95% CI)	Forest plot of pooled mean differences with 95% CI	Number of studies	Total n	Heterogeneity: I²	Test for subgroup differences: p-value
2D digital imaging technologies	Female	-0.68 (-1.98–0.61)		3	623	44%	0.86
	Male	-0.92 (-3.27–1.44)		3	556	71%	
Relative fat mass (RFM)	Female	-0.23 (-1.37–0.91)		8	18,004	97%	0.16
	Male	0.77 (-0.01–1.54)		9	15,683	94%	
Body adiposity index (BAI)	Female	-2.20 (-4.15– -0.25)		29	21,041	100%	<0.01
	Male	2.55 (-0.00–5.11)		28	10,317	100%	
3D body scanners	Female	-1.33 (-3.78–1.12)		3	723	92%	0.80
	Male	-1.90 (-5.48–1.67)		3	584	96%	

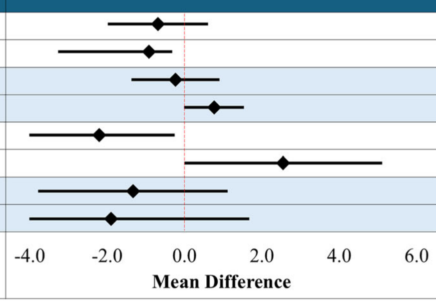

FIGURE 5 Summary of *pooled mean differences* for each non-traditional obesity measure that was evaluated at more than one life stage, compared to total body fat percentage measured from a reference standard, by sex subgroup.

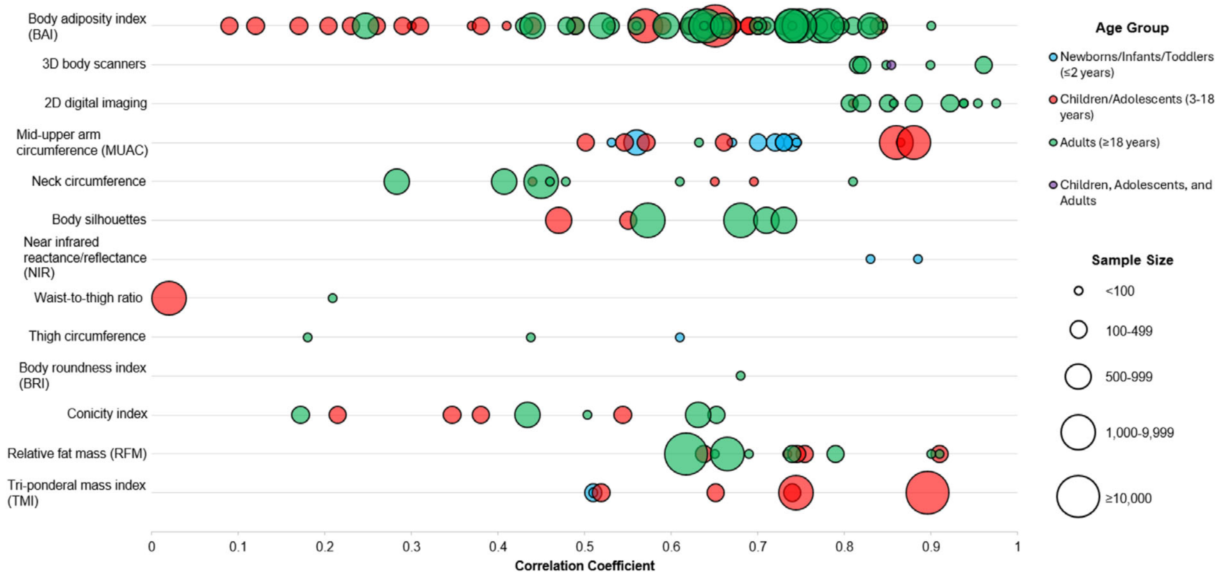

FIGURE 6 Bubble plot of Spearman and Pearson correlation coefficients for the 13 non-traditional obesity measures evaluated at multiple life stages, compared to total body fat as the reference standard, with age group and sample size categories.

also not conducted for the TMI due to the inclusion of only two studies which each used different reference standard units, as well as for the BAI and MUAC where all reference standards were reported in percent across included studies. For 2D digital imaging technologies, there was no evidence of a standardized mean difference (SMD = -0.06; 95% CI: −0.12–0.00; $n = 2358$; nine studies; $I^2 = 3\%$) (Figure S31). Additionally, there was no statistically significant difference among males and females ($p = 0.77$) (Figure S32).

3.3.11 | Other non-traditional measures evaluated at multiple life stages

Studies evaluating the BRI ($n = 2$), waist-to-thigh ratio ($n = 2$), thigh circumference ($n = 3$), NIR ($n = 2$), and pictorial body silhouettes ($n = 4$) at multiple life stages were not meta-analyzed. A bubble plot of correlation coefficients for the 13 measures evaluated at multiple life stages is presented in Figure 6. Three studies evaluating pictorial body silhouettes reported correlation coefficients, which ranged from low to moderate and were greater among adults.[40,94,145] For thigh circumference, two studies among adults demonstrated negligible to low correlations, while the study among newborns demonstrated a moderate correlation.[54,136,144] For waist-to-thigh ratio, a study among adults and a study among children both found negligible correlations.[125,136] One of the two studies reported correlation coefficients for NIR, which indicated a high correlation in infants/toddlers.[63] One of the two studies evaluating the BRI reported a correlation coefficient, which was moderate among adults.[144] In addition to the negligible or low correlations <0.4 observed for waist-to-thigh ratio and thigh circumference, the BAI, neck circumference, and the conicity index also had studies that observed correlations <0.4.

3.4 | Quality assessment

Quality assessment was completed for the 104 studies that included any of the 13 non-traditional obesity measures validated at multiple life stages (Figure 7, Table S4). Risk of bias for the index test ($n = 98$) and reference standard ($n = 92$) domains were primarily low. Nearly half of studies ($n = 50$) had a high risk of bias for the patient selection domain, since they used non-probability sampling or excluded participants based on size (e.g., weight, BMI). Risk of bias for the flow and timing domain was low for most studies ($n = 60$), but 25 studies were unclear, and 19 studies had a high risk of bias if participants were enrolled in the study but did not receive both measures and were excluded from the analysis. For concerns regarding applicability, most studies had low concerns for both the patient selection ($n = 58$) and index test ($n = 65$) domains. For the patient selection domain, 44 studies had high concerns based on the generalizability of the included participants. For the index test domain, 39 studies had high concerns when the non-traditional measure was similar to traditional obesity measurements, did not align with the WHO definition of obesity, or required specialized equipment.

4 | DISCUSSION

This systematic review identified 55 validated non-traditional measures of obesity. However, the majority were focused on anthropometric measurements and did not consider health risks associated with increased adiposity. Of the 55 measures identified, 13 were evaluated at multiple life stages and 8 of these were meta-analyzed. Our review primarily focused on the measures that were validated at multiple life stages to better understand their use from a life course perspective. High or moderate validity (pooled correlation coefficient

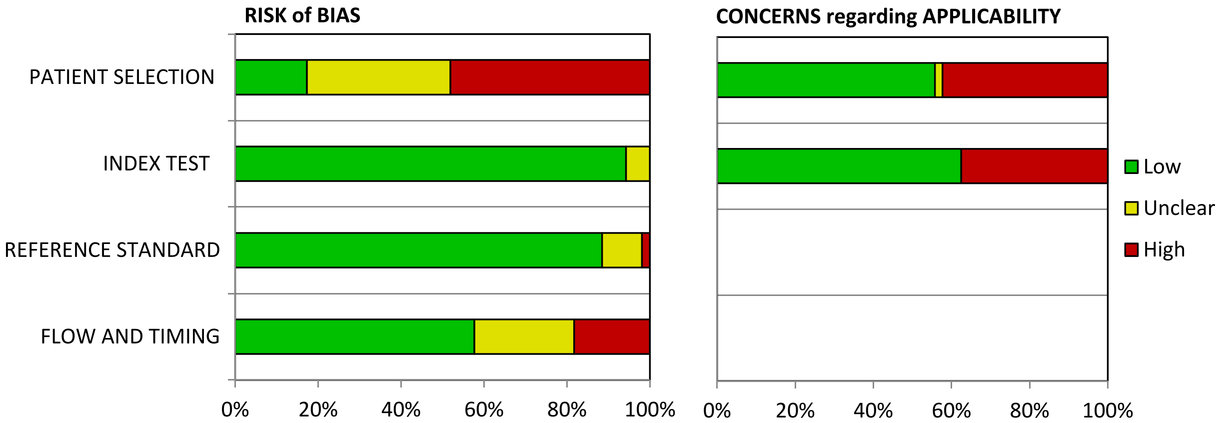

FIGURE 7 Summary of risk of bias and concerns regarding applicability assessment using the QUADAS-2 tool, for studies included in the validity and reliability measurement extraction phase only ($n = 104$).

>0.70) was observed for 2D digital imaging technologies, 3D body scanners, RFM, and MUAC. Differences in the validity by life stages were observed for the TMI and the BAI. Results of the meta-analyses for mean differences suggested small mean differences between reference standard measures of total body fat percentage and RFM, 2D digital imaging technologies, 3D body scanners, and the BAI, and was unlikely to be clinically relevant. Differences by life stages were observed for the BAI and RFM. Differences by sex were observed for the BAI. High heterogeneity was observed in most of our meta-analyses and limited subgroup analysis was feasible due to data availability. Potential sources of heterogeneity were inconsistencies in the reference standards, variations in the study populations, and different devices/applications and methods (i.e., for the 2D digital imaging technologies and 3D scanners). High heterogeneity limits the reliability of the pooled estimates and conclusions of our study. Thus, results should be interpreted with caution.

There is a need to evaluate obesity beyond weight and anthropometric measurements. However, numerous non-traditional obesity measures identified in our review can be measured in population health and clinical settings using anthropometrics. WHO defines obesity as "abnormal or excessive fat accumulation that presents a risk to health"[1] but most of the non-traditional measures identified in this study did not align with this definition. Firstly, the measures did not directly measure total body fat. However, there were some validated measures that estimated total body fat in our study, connecting to the "excessive fat accumulation" component of the WHO definition of obesity. This included measures such as 3D body scanners, 2D digital imaging technologies, the BAI, and RFM. The ability of these and other non-traditional measures to estimate total body fat percentage increases their applicability for use, and with high validity, may decrease misclassification that occurs when using BMI as a sole measure of adiposity.[12,13] In our meta-analyses, 3D body scanners, 2D digital imaging technologies, the BAI, and RFM demonstrated moderate to high correlations and small mean differences that were unlikely to be clinically relevant. While excess total body fat is a cardiometabolic risk factor, visceral adiposity is most strongly associated with cardiometabolic risk and chronic illness,[16,17] and the validity of the non-traditional obesity measures identified in our review in relation to visceral adiposity needs to be explored.

Secondly, the majority of measures identified in our review did not involve health assessment, although classifications that emphasize health risks exist. The Edmonton Obesity Staging System (EOSS)[155–157] and EOSS for Pediatrics (EOSS-P)[158,159] accounts for the presence of comorbidities, functional limitations, and mental health decline to determine the severity of obesity; however, only one study among adults included in our review evaluated the EOSS. Another measure identified in our review in one study among adults that considers health is the visceral adiposity index (VAI), which includes a combination of BMI, waist circumference, triglycerides, and high-density lipoprotein levels. There are other classifications that consider health assessment that were not identified in our review. For example, distinguishing between phenotypes such as metabolically healthy obesity and metabolically unhealthy obesity considers cardiometabolic health.[160,161] The adiposity-based chronic disease (ABCD) framework also considers health and encompasses the amount, distribution, and function of adiposity as well as physical and cultural contexts that together, result in the development of adiposity-based complications and disease stages.[162,163] The European Association of the Study of Obesity (EASO) has also called for more comprehensive criteria for diagnosing obesity, and have proposed a diagnostic and classification scheme that is based on three dimensions including etiology, degree of adiposity, and health risk.[164] More research is needed to define valid obesity measures across the life course that incorporate both excess adiposity and assess health risk.

Most of the identified non-traditional measures in our meta-analyses had relatively low participant burden and were highly accessible, except for measures that require specialized equipment, such as 3D body scanners. Many of the identified measures were attainable through anthropometry, which usually requires trained staff for valid data collection. 2D digital imaging technology such as smartphone applications are relatively unique in that they have potential as a measure that may be feasible for remote data collection by participants

TABLE 3 Summary of the advantages and disadvantages of the eight non-traditional obesity measures that were meta-analyzed in our study.[a]

Non-traditional obesity measure	Low participant burden	Highly accessible	Moderate to high validity (pooled correlation coefficient >0.70)	Validated among all 3 life stages	Feasible for population-based studies with no direct participant contact	Considers health risks associated with excess adiposity	Estimates total body adiposity
2D digital imaging technologies	+	+	+	–	+	–	+
3D body scanners	–	–	+	–	+	–	+
Mid-upper arm circumference (MUAC)	+	+	+	+	–	–	–
Neck circumference	+	+	–	–	–	–	–
Relative fat mass (RFM)	+	+	+	–	–	–	+
Tri-ponderal mass index (TMI)	+	+	–	+	–	–	–
Body adiposity index (BAI)	+	+	–	–	–	–	+
Conicity index	+	+	–	–	–	–	–

[a]Green boxes with + indicate advantages, and red boxes with – indicate disadvantages.

without direct measurement by trained staff, though more research is needed to evaluate the validity among life stages other than adults. The advantages and disadvantages of these measures are summarized in Table 3.

Many of the validated non-traditional anthropometric measures identified in our study have also been identified in other reviews.[10,11] However, some measures may not have been included in our review if they were not validated against one of the total body fat reference standards we defined in our study. Evidence from a systematic review has suggested that MUAC accurately identified obesity among children and adolescents.[165] However, BMI was primarily used as the reference standard among included studies,[165] which may explain why our review found a moderate correlation. Similarly, a systematic review suggested that neck circumference was an accurate measure of obesity,[166] which differs from our findings of a low correlation with total body fat. However, the review only included studies with BMI as the reference standard,[166] which might explain this difference. Two reviews have found conflicting evidence regarding the validity of the BAI for estimating total body fat among adults, with one review concluding it is valid[167] and the other review concluding it has limitations and is not a valid measure of body fat percentage.[168] Our review found no evidence of a mean difference and a moderate correlation. Evidence has suggested that TMI correlated with body fat better than BMI among children and adolescents.[169] Although it was not compared to BMI in our review, we found that TMI had a moderate correlation with total body fat among children and adolescents.

4.1 | Strengths and limitations

Strengths of our review include the identification of a variety of non-traditional obesity measures, including those that go beyond anthropometrics since these address some of the limitations of traditional measures, such as BMI.[12,18] The validity of the included measures were evaluated by comparison to accurate reference standards for measuring body composition.[25] Furthermore, our review included studies from numerous continents and various life stages, which enhances the generalizability of our findings.

Potential limitations of our review include that it was difficult to encompass the broad WHO definition of obesity and non-traditional measures of obesity in our search. For instance, there are no specific search terms that indicate non-traditional measures of obesity or excessive adiposity that present health risks. The search was also limited to studies in English. Additionally, not all studies for each measure evaluated were included in meta-analyses due to insufficient data. For 2D digital imaging technologies and 3D body scanners, we did not evaluate individual components or different applications/devices separately, and we considered complete final products only. Although we provided subgroup analyses by life stage and sex, we could not conduct subgroup analyses by race or ethnicity because many included studies did not stratify by race or ethnicity. Additionally, for included studies conducted among children and/or adolescents, we could not assess validity by stage of puberty because the stage was not determined, or stratification was not available. Many studies also included both children and adolescents in the study sample and we could not evaluate these life stages in isolation.

5 | CONCLUSION

In conclusion, our systematic review identified non-traditional measures of obesity that have moderate to high validity at multiple life stages, compared to total body fat reference standards, including 2D digital imaging technologies, 3D body scanners, RFM, and MUAC. While these measures were not directly compared to BMI, they may more accurately measure body fat and may also have the advantage of being easy to use for both population-based studies or in low-resource settings. 2D digital imaging technologies had particularly high validity and applicability for use among general populations. Other measures validated at multiple life stages included the TMI, neck circumference, the conicity index, and the BAI. However, the results should be interpreted with caution due to high heterogeneity in most meta-analyses. More research on non-traditional measures at each life stage is needed to understand whether non-traditional measures contribute to the measurement of obesity across the life course. Future research is needed to define valid obesity measures across all life stages that assess health outcomes in addition to adiposity. For example, this may include measures that focus on health impairments, physical function, and well-being in combination with measures of body fat.

CONFLICT OF INTEREST

None of the authors declare any conflicts of interest.

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