Anthropometric indices in predicting 10-year cardiovascular risk among males and females aged 40–74 years in south and southeast Asia: analysis of 12 WHO STEPS survey data

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Summary

Background The relevance of anthropometric indices in predicting cardiovascular disease (CVD) or CVD risk factors is established across different countries, particularly in the high-income countries. However, past studies severely lacked representation from the south and southeast Asian countries. The main aim of this study was to determine the performance of conventional and new anthropometric indices to best predict 10-year cardiovascular disease (CVD) risk in south Asian and southeast Asian populations.

Methods The present study examined data from 14,532 participants in three south Asian and 13,846 participants (all aged between 40 and 74 years) in six southeast Asian countries, drawn from twelve cross-sectional studies (WHO STEPwise approaches to NCD risk factor surveillance [STEPS] survey data from 2008 to 2019). A Predictive performance of ten anthropometric indices were examined for predicting 10-year CVD risk ≥ 10% (CVD-R ≥ 10%). The 10-year CVD-R ≥ 10% was calculated by utilising the WHO CVD risk non-laboratory-based charts. Receiver operating characteristic (ROC) curve analysis was used to identify the optimal anthropometric index.

Findings Among the ten anthropometric indices, a body shape index (ABSI), body adiposity index (BAI), body roundness index (BRI), hip index (HI), and waist-height ratio (WHtR) performed best in predicting 10-year CVD risk among south Asian males and females. Improved performances were found for ABSI, BRI, conicity index (CI), WHtR, and waist-hip ratio (WHR) for 10-year CVD-R ≥ 10% predictions among southeast Asian males. Contrastingly, among southeast Asian females, ABSI and CI demonstrated optimal performance in predicting 10-year CVD-R ≥ 10%.

Interpretation The performance of anthropometric indices in predicting CVD risk varies across countries. ABSI, BAI, BRI, HI, and WHtR showed better predictions in south Asians, whereas ABSI, BRI, CI, WHtR, and WHR displayed enhanced predictions in southeast Asians.

Funding None.

Keywords: Anthropometry indices; Cardiovascular disease risk; south Asia; southeast Asia; Receiver operating characteristic (ROC) curve analysis

Introduction

Nutrition transition has shifted the global burden of diseases from infectious to non-communicable diseases (NCDs), where cardiovascular disease (CVD) accounts for a major proportion of disabilities and deaths due to NCDs.[1] Globally, around 523 million people had CVD in

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Research in context

Evidence before this study

Previous research examining anthropometric indices and cardiovascular diseases (CVDs) risk primarily focused on evaluating indices against individual CVD risk factors like elevated blood pressure, blood glucose, and dyslipidaemia or studying specific CVD manifestations such as ischaemic heart disease. In contrast, some Iranian and Chinese studies attempted to identify the best index for predicting CVD risk by examining their performances against the 10-year risk of CVD. However, no studies have yet compared the performance of anthropometric indices against country-specific 10-year CVD risk, calculated using WHO CVD risk charts. Our literature search (the earliest available date to March 1 2024) on PubMed and Google Scholar confirmed this gap, using the following terms: 'Anthropometric indices' AND 'Cardiovascular disease' AND 'WHO' AND 'Cardiovascular disease risk charts'. Furthermore, a recent systematic review titled "Discriminatory Capacity of Anthropometric Indices for Cardiovascular Disease in Adults: A Systematic Review and Meta-Analysis" did not include any studies matching the context and method of our study.

Added value of this study

We used data from the WHO STEPwise approach to surveillance (STEPS) surveys to show the performance of anthropometric indices to predict the 10-year risk of CVD for nine south and southeast Asian countries. This study also marks one of the earliest explorations to compare the performance of ten anthropometric indices in south and southeast Asian countries to predict CVD risk. For most countries, there was no prior information on the performance of nine anthropometric indices and their relation to CVDs.

Implications of all the available evidence

The performance of anthropometric indices in predicting CVD risk exhibits variation across different south and southeast Asian countries. Our findings indicate that BMI, commonly employed in south and southeast Asian countries for CVD prediction, is not the most reliable predictor. This underscores the need for further prospective studies to validate our results. Enhanced accuracy in predicting CVD risk is crucial for developing more effective intervention strategies, aligning with the goal of reducing premature mortality from non-communicable diseases (Sustainable Development Goal 3.4).

2019 and the years lived with disability increased to 34.4 million in 2019, from 17.7 million in 1990.[1]

Numerous studies have established the relevance of anthropometric indices in predicting CVD or CVD risk factors across different countries, particularly in high-income countries.[2–4] BMI is a widely used anthropometric index recommended by the WHO to define obesity. However, the discriminating power of BMI as CVD or as a CVD risk factor predictor was found to be lower compared to waist circumference (WC). Similarly, a lower distinguishing capacity was found for BMI compared to waist-height ratio (WHtR) in distinguishing individuals with high muscle mass from those with excess fat or abdominal obesity.[2] Furthermore, two systematic evaluations demonstrated that WHtR could be a more accurate predictor of CVD compared to BMI and WC.[3,4] Moreover, recently developed novel indices, including a body shape index (ABSI), abdominal volume index (AVI), body adiposity index (BAI), body roundness index (BRI), conicity index (CI), and hip index (HI), which are calculated from simple measurements of weight, height, WC, and hip circumference (HC), were considered to be better than BMI, at predicting CVD risk factors or CVD.[5]

However, past studies severely lacked representation from south and southeast Asian countries. Moreover, thus far no emphasis has been placed on the clinical significance of these anthropometric indices in assessing and stratifying CVD risk across south Asian and southeast Asian populations. Previous research projects aimed to identify the best anthropometric index for predicting CVD were predominantly centered on assessing the performance of anthropometric indices on individual CVD risk factors, such as elevated blood pressure, heightened blood glucose levels, and dyslipidaemia or specific CVD manifestations like ischaemic heart disease.[2–4] On the other hand, research conducted in Iran and China attempted to identify a suitable anthropometric index by investigating anthropometric index performance with regard to a 10-year CVD risk.[6,7] Presently, there is a noticeable absence of research delving into the association between anthropometric indices and the broader scope of long-term CVD risk, particularly in the context of south and southeast Asia.

The primary objective of the present study was to assess the predictive capacity of ten anthropometric indices (ABSI, AVI, BAI, BMI, BRI, CI, HI, WC, WHtR, and WHR) in estimating the 10-year CVD risk in south and southeast Asian countries. Further this study explored the relationship of anthropometric indices with 10-year CVD risk. This investigation focused on males and females from south Asian (Bangladesh, Nepal, and Pakistan) and southeast Asian (Cambodia, Maldives, Laos, Myanmar, Timor-Leste, and Vietnam) populations. The current study aimed to calculate the 10-year CVD risk using WHO CVD risk non-laboratory-based charts (WHO-CVD-NL-C). This scoring system has been validated for south Asian and southeast Asian populations and can be used to calculate CVD risk scores using the available data for the regions.[8] Furthermore, this study tested the performance of anthropometric indices in predicting CVD risk for the selected countries by comparing them against the 10-

year CVD risk calculated using WHO CVD risk laboratory-based charts (WHO-CVD-L-C).

Methods

Study design, setting, and sampling

The current study utilised twelve WHO STEPwise approaches to NCD risk factor surveillance (STEPS) survey data from south and southeast Asian countries (Fig. 1), available through WHO NCD Microdata Repository[9] (link to website is provided under 'Data sharing statement'). These surveys were conducted between 2006 and 2019 in nine south and southeast Asian countries, including Bangladesh, Cambodia, Maldives, Nepal, Myanmar, Lao People's Democratic Republic, Pakistan, Timor-Leste, and Vietnam. All the surveys were nationally representative except those conducted in Pakistan, the Maldives, and Laos (2008) (Supplementary Table S1). STEPS is a standardised yet adaptable framework by the WHO that allows countries to track key risk factors of NCDs. It involves surveys conducted by national authorities. STEPS acknowledges the need for both consistent data collection and flexibility to suit different countries. The framework offers various levels of risk factor assessment depending on available resources while ensuring data comparability. STEPS relies on surveys of adults (aged 18–69 years) within households, using a two-stage, stratified probability-based sampling approach. Sample sizes are tailored to each country based on factors like the level of confidence, the acceptable margin of error, the estimated design effect, the estimated baseline levels of the behaviours to be measured, the desired number of age–gender estimates, and the anticipated nonresponse rate.[9] The detailed methodology, sample size calculation, and sample collection procedure for each country are available elsewhere.[9] The findings of this study are reported following the Standards for Reporting Diagnostic Accuracy Studies (STARD) guideline (Supplementary Table S2).

Data collection

The survey in each country was conducted via face-to-face interviews using a standardised questionnaire guided by the WHO STEPS manual. STEP I included questions on sociodemographic (for example, age and sex) and modifiable risk factors such as tobacco use. STEP II covered physical measurements, including height, weight, waist circumference, hip circumference, and blood pressure; STEP III was related to biological measurements, including fasting blood glucose and total cholesterol level.[9]

Most surveys employed consistent methods for measuring height, weight, waist, and hip circumference.[9] Measurement tools included a portable stadiometer for height measurement, a portable weighing scale for weight measurement, and a constant-tension tape for waist and hip circumferences. For height measurement, Nepal utilised a portable standard stature tape in 2019. Standard procedures involved participants removing footwear and any headwear for height measurement. They stood on the stadiometer facing the interviewer with proper posture (feet together, knees straight, head level with eyes aligned to ears). For weight measurement, the scale was placed on a firm, level surface. Participants stood on the scale with light clothing, one foot on each platform, and arms relaxed. The waist was measured at the end of a normal exhalation, midway between the lower rib and the hip bone's top ridge (top of the iliac crest). Hip circumference was taken at the maximum circumference over the buttocks.[9]

In all surveys, participants' blood pressure was measured using automated blood pressure monitors, except in Bangladesh (2009), where aneroid sphygmomanometers were used. Three readings were taken in each survey, and the mean of the second and third readings was used for analysis. For blood glucose and total cholesterol measurement, most surveys relied on capillary blood and handheld point-of-care devices (Cardiocheck Pa, Accutrend Plus, or SD Lipidocare analyzers). Only Bangladesh (2018) and Nepal (2012) used venous blood samples analysed by biochemistry auto analysers.[9]

Analytic sample construction

The inclusion criteria of a country STEPS survey data in this study were as follows.

(i) the survey was conducted in the south or southeast Asian region, based on the classification used during the development of WHO-CVD-NL-C,[8]
(ii) the survey data were available at the individual level,
(iii) the survey contained individuals aged 40–74 years, not pregnant during the interview, and with no history of atherosclerotic cardiovascular disease (ASCVD) events (stroke or heart attack),
(iv) data to calculate anthropometric indices were available,
(v) data required to develop CVD scores based on WHO-CVD-NL-C were available.

A schematic diagram of the study population is demonstrated in Fig. 1, separately for the south (A) and southeast (B) Asian regions. The current study further investigated the variables required to calculate risk using WHO-CVD-L-C based on data availability for each country. It is important to note that there was no representation from Pakistan and the Maldives in the development of the WHO-CVD-L-C due to the unavailability of a specific variable, namely, total cholesterol (Supplemental Figure S1).

CVD risk estimation

The 10-year risk for CVD events was calculated separately for each country among south and southeast Asian males and females using both WHO-CVD-NL-C and WHO-CVD-L-C. WHO-CVD-NL-C and WHO-

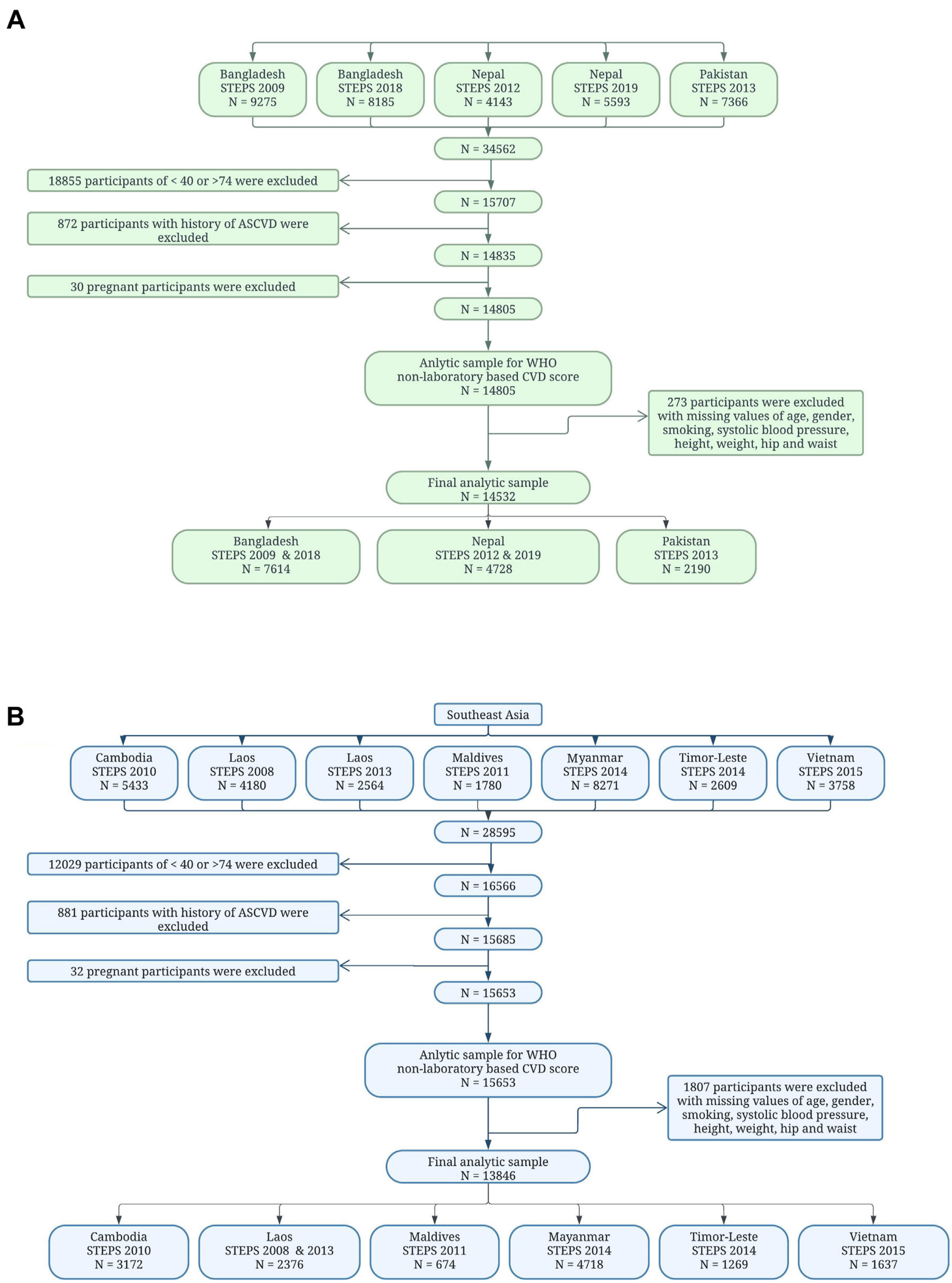

Fig. 1: **A schematic diagram of the construction of the analytic sample for WHO non-laboratory based CVD score. (a) South Asia (b) southeast Asia. ASCVD: atherosclerotic cardiovascular disease; CVD: cardiovascular diseases.**

CVD-L-C were developed for twenty-one regions globally, including the south and southeast Asian region, to estimate the risk of fatal or non-fatal CVD events, such as myocardial infarction and stroke, in a ten-year period.[8] Both charts can provide a CVD risk score for individuals aged 40–74 years. The parameters required to calculate the CVD risk score using WHO-CVD-NL-C were age (in years), sex (male vs. female), smoking status (no vs. yes), BMI, and systolic blood pressure (SBP) in mmHg. On the other hand, the parameters required to calculate the CVD risk score using WHO-CVD-L-C were age (in years), sex (male vs. female), smoking status (no vs. yes), diabetes status (no vs. yes), total cholesterol (mmol/L), and systolic blood pressure (SBP) in mmHg.[8] The risk stratification for both WHO-CVD-NL-C and WHO-CVD-L-C are as follows: <5% (green), 5% to <10% (yellow), 10% to <20% (orange), 20% to <30% (red), and ≥30% (dark red).[8] Considering the limited scope and sample size, this study calculated CVD risk≥10% (CVD-R ≥ 10%) by sex and country.

Anthropometric indices

This study tested the performance of ten anthropometric indices to best predict 10-year CVD-R ≥ 10% among south and southeast Asian populations. The following formulas were used to calculate ABSI, AVI, BAI, BMI, BRI, CI, HI, WC, WHR, and WHtR.

$$\text{ABSI: } \frac{waist\ circumference(m)}{BMI^{\frac{2}{3}} \times height(m)^{\frac{1}{2}}}$$

$$\text{AVI: } \left\{2 \times waist\,circumference(cm)^2 + 0.7 \times \left[waist\,circumference(cm) - hip\,circumference(cm)\right]^2\right\} / 1000$$

$$\text{BAI} = \frac{hip\,circuference(cm)}{height(m) \times \sqrt{height(m)}} - 18$$

$$\text{BMI: } weight(kg) / height(m)^2$$

$$\text{BRI} = 364.2 - \left(365.5 \times \sqrt{1 - \left(\frac{\left(waist\,circumference(m)/2\pi\right)^2}{\left(0.5 \times height(m)\right)^2}\right)}\right)$$

$$\text{CI: } waist\,circumference(m) \Bigg/ \left[0.109 \times \frac{\sqrt{weight(kg)}}{height(m)}\right]$$

$$\text{HI: } hip\ circumference\ (cm) \times \left(\frac{height(cm)}{[H]}\right)^{0.310} \times \left(\frac{weight(kg)}{[w]}\right)^{0.482}$$

where height [H] = 166 cm and weight [W] = 73 kg are average values included in the definition as scaling factors.[5]

$$\text{WHR: } waist\ circumference(cm) / hip\ circumference(cm)$$

$$\text{WHtR: } waist\ circumference(cm) / height(cm)$$

Statistical analysis

All analyses were separately conducted for each study country in the south and southeast Asian regions. Continuous data were reported with mean and SD, and categorical data as the frequency with proportion. Means were compared across countries using ANOVA, and proportions were compared using logistic regression, with adjustments for age and sex. Pearson's linear correlation analysis was used to determine both correlation coefficients among raw anthropometric indices and the correlation of z-scores (adjusted for age and sex) for the anthropometric indices. 10-year CVD-R ≥ 10% was calculated for both WHO-CVD-NL-C and WHO-CVD-L-C. The Kappa coefficient was obtained to test interrater reliability between WHO-CVD-NL-C and WHO-CVD-L-C by country and sex and interpreted according to Cohen's suggestion.[10] Areas under the curves (AUCs) were computed to determine the discriminatory accuracy of each of the ten obesity measures (ABSI, AVI, BAI, BMI, BRI, CI, HI, WC, WHtR, and WHR) in the diagnosis of the individuals with 10-year CVD-R ≥ 10%. An AUC of 1 reflects a perfect predictive capability, whereas an AUC ≤0.5 suggests that the discriminatory power is no better than chance. Among anthropometric indices, those with the highest AUC values from ROC analyses were identified as the best-performing anthropometric indices to predict 10-year CVD-R ≥ 10% in individuals. Further sensitivity, specificity, and the Youden index were calculated for the best performer, where optimal cut-offs were defined as the values of the indicators that maximised the Youden index (J = sensitivity + specificity–1). DeLong's method was utilized to analyse the significance of the AUC when comparing different anthropometric indices. The study further calculated odds ratios (OR) with 95% CI to examine the associations between best-performing anthropometric indices and the 10-year CVD-R ≥ 10%. Notably, to address dimensional differences, a z-score transformation was applied to the ten anthropometric indices in regression analysis. Analyses were performed with STATA version 17.0 (basic edition), and the results were graphically represented using the ggplot2 package of R 4.3.1. The roccomp (ROC regression) package of Stata software was used to create the ROC curves and related comparisons. p values less than 0.05 were considered as statistically significant.

Ethical considerations

All individual STEPS surveys received ethical approval from country-specific ethics review boards. Before data collection, written informed consent was obtained from the participants. Permission was obtained to use the dataset from the NCD Microdata Repository of WHO in January 2022. De-identified data were used for analysis, so this study was exempted from review by the institutional review board.

Role of the funding source

There was no funding source for this study.

Results

Background characteristics of the participants

The demographic details, anthropometric measurements, and blood pressure data of participants are presented in Table 1 based on the analytic sample constructed to calculate 10-year CVD-R ≥ 10% utilising WHO-CVD-NL-C. All the variables reported in Table 1 showed statistically significant ($p < 0.0001$) differences across countries after adjusting for age and sex. The highest mean BMI was observed among participants from the Maldives (27.0), while the lowest mean BMI was noted among participants from Laos (20.9). Timor-Leste had the highest (36.1%), whereas the Maldives had the lowest smoking prevalence (14.7%). Supplemental Table S3 demonstrates the demographic details, anthropometric measurements, and blood pressure data of participants based on the analytic sample constructed to calculate 10-year CVD-R ≥ 10% utilising WHO-CVD-L-C.

Correlation coefficients among anthropometric indices

Supplemental Table S4a presents correlation coefficients for all south Asian and southeast Asian countries (based on the analytic sample constructed for WHO-CVD-NL-C) among ten anthropometric indices using both raw values and z-scores after adjusting for age and sex. Z-scores of AVI, BAI, BRI, WC, WHtR, and WHR all exhibited positive correlations with BMI z-scores across all countries and was statistically significant ($p < 0.05$). ABSI and HI z-scores were negatively correlated with BMI z-scores in most countries (statistically significant, $p < 0.05$) except Cambodia and the Maldives. In Cambodia, the correlation between ABSI and BMI z-scores was negative but not statistically significant ($p = 0.09$). Conversely, Maldives showed a significant positive correlation ($p < 0.05$) between HI and BMI z-scores. The correlation between CI and BMI varied across countries. A significant positive correlation ($p < 0.05$) was observed in Bangladesh, Nepal, Cambodia, Vietnam, and Maldives. In contrast, Pakistan, Laos, Myanmar, and Timor-Leste showed negative correlations, with only Myanmar reaching statistical significance ($p = 0.001$). Notably, a very strong and significant positive correlation ($r > 0.9$, $p < 0.05$) was observed between BRI and WHtR, ABSI and CI, and AVI and WC across all south Asian and southeast Asian countries. Supplementary Table S4b presents correlation coefficients for all south Asian and southeast Asian countries based on the analytic sample constructed for WHO-CVD-L-C.

Variables	South Asia			Southeast Asia					
Characteristic, mean ± SD/n (%)	Bangladesh (n = 7614)	Nepal (n = 4728)	Pakistan (n = 2190)	Cambodia (n = 3172)	Laos (n = 2376)	Myanmar (n = 4718)	Timor-Leste (n = 1269)	Vietnam (n = 1637)	Maldives (n = 674)
Age (years)[a]	51.0 ± 8.4	52.1 ± 8.6	50.5 ± 8.6	50.7 ± 6.9	50.0 ± 6.9	51.1 ± 7.0	52.5 ± 9.2	52.2 ± 8.1	51.5 ± 7.2
Current smoker[a]	2228 (29.3)	1224 (25.9)	432 (19.7)	748 (23.6)	634 (26.7)	1225 (26.0)	458 (36.1)	414 (25.3)	99 (14.7)
SBP (mmHg)[a]	125.0 ± 20.7	132.8 ± 21.0	135.2 ± 20.7	119.1 ± 18.5	127.2 ± 21.5	130.7 ± 22.7	130.6 ± 21.9	126.8 ± 20.9	136.8 ± 23.6
Height (cm)[a]	156.3 ± 8.9	154.0 ± 8.5	159.3 ± 9.7	154.7 ± 7.1	155.6 ± 8.2	156.7 ± 8.9	155.0 ± 8.8	155.6 ± 7.8	153.7 ± 9.1
Weight (kg)[a]	54.1 ± 12.5	55.1 ± 11.6	64.3 ± 15.6	52.9 ± 9.9	57.4 ± 12.6	56.2 ± 12.1	50.4 ± 10.2	54.8 ± 9.3	63.6 ± 11.5
WC (cm)[a]	79.1 ± 11.9	81.4 ± 11.7	87.6 ± 15.1	77.3 ± 9.9	79.0 ± 15.6	79.3 ± 11.7	76.7 ± 10.4	79.0 ± 9.1	89.9 ± 13.3
HC (cm)[a]	88.7 ± 9.4	89.6 ± 10.5	96.2 ± 13.7	89.2 ± 7.3	89.6 ± 15.6	92.3 ± 11.2	85.2 ± 13.2	90.9 ± 6.5	98.0 ± 11.7
BMI[a]	22.1 ± 4.8	23.2 ± 4.5	25.4 ± 6.4	22.0 ± 3.7	23.7 ± 5.0	23.0 ± 9.2	20.9 ± 7.7	22.6 ± 3.3	27.0 ± 4.9
WHtR[a]	0.5 ± 0.07	0.5 ± 0.07	0.5 ± 0.09	0.5 ± 0.06	0.5 ± 0.1	0.5 ± 0.08	0.5 ± 0.06	0.5 ± 0.05	0.5 ± 0.09
WHR[a]	0.9 ± 0.08	0.9 ± 0.08	0.9 ± 0.08	0.9 ± 0.06	0.9 ± 0.09	0.8 ± 0.09	0.9 ± 0.09	0.9 ± 0.07	0.9 ± 0.1
AVI[a]	12.9 ± 3.9	13.6 ± 3.9	15.9 ± 5.4	12.2 ± 3.1	13.1 ± 4.4	13.0 ± 4.1	12.1 ± 3.6	12.8 ± 2.8	16.6 ± 5.2
BAI[a]	27.6 ± 6.0	29.1 ± 6.3	30.1 ± 8.1	28.4 ± 4.5	28.4 ± 8.6	29.4 ± 8.6	26.3 ± 7.6	29.0 ± 4.3	33.9 ± 8.1
BRI[a]	3.6 ± 1.5	4.0 ± 1.5	4.5 ± 2.1	3.4 ± 1.3	3.7 ± 1.7	3.6 ± 2.1	3.4 ± 1.3	3.6 ± 1.2	5.3 ± 2.2
ABSI[a]	0.081 ± 0.006	0.081 ± 0.008	0.081 ± 0.01	0.08 ± 0.005	0.08 ± 0.01	0.08 ± 0.008	0.081 ± 0.008	0.08 ± 0.005	0.08 ± 0.008
CI[a]	1.2 ± 0.1	1.2 ± 0.1	1.3 ± 0.2	1.2 ± 0.08	1.2 ± 0.2	1.2 ± 0.1	1.2 ± 0.1	1.2 ± 0.9	1.3 ± 0.1
HI[a]	101.5 ± 6.4	100.9 ± 8.9	102.0 ± 11.0	102.5 ± 4.6	99.3 ± 15.9	103.5 ± 8.7	100.4 ± 14.1	102.8 ± 4.5	102.7 ± 9.1

Abbreviations: ABSI, a body shape index; AVI, abdominal volume index; BAI, body adiposity index; BRI, Body roundness index; CI, conicity index; HC, hip circumference; HI, Hip index; SBP, systolic blood pressure; WC, waist circumference; WHR, waist-to-hip ratio; WHtR, waist-to-height ratio; WHO-CVD-NL-C; WHO CVD risk non-laboratory-based charts. [a]Statistically significant differences ($p < 0.05$) were observed across countries for continuous variables (ANOVA adjusted for age and sex) and categorical variables (logistic regression adjusted for age and sex), while the analysis for age was sex-adjusted only.

Table 1: **Characteristics of the south Asian and southeast Asian participants based on the analytic sample constructed for WHO-CVD-NL-C.**

10-year CVD risk of the participants

Fig. 2a and b show the prevalence of 10-year CVD-R ≥ 10% in south Asian and southeast Asian countries based on WHO-CVD-NL-C. In all countries, males had a higher prevalence of 10-year CVD-R ≥ 10% compared to females. In comparison to Bangladesh and Pakistan, males and females in Nepal had the highest prevalence of 10-year CVD-R ≥ 10%. In southeast Asia, Timor-Leste displayed the highest prevalence of 10-year CVD-R ≥ 10% among males, with a rate of 26.4%, while the highest prevalence among females was observed in the Maldives, where the rate estimated was 9.7%. There was a slight variation in the prevalence of 10-year CVD-R ≥ 10% between the WHO-CVD-NL-C and WHO-CVD-L-C method (Supplementary Figure S2) in the selected countries of both regions. However, the Kappa coefficients were found to show substantial (>0.7) to moderate agreement (>0.4) between the estimation of methods for the 10-year CVD-R ≥ 10% among males and females of those selected countries (Supplementary Table S5).

Result

Comparison of the predictive performance of anthropometric indices

Fig. 3 shows the predictive performance of ten anthropometric indices among south Asian (Bangladesh, Nepal, and Pakistan) males and females based on the ROC curve analysis compared to risk estimated using WHO-CVD-NL-C. In Bangladesh, ABSI exhibited higher predictive accuracy than other anthropometric indices in predicting 10-year CVD-R ≥ 10% among both males (AUC = 0.595) and females (AUC = 0.584). It differed across sexes in Nepal and Pakistan. In Nepalese males, ABSI and BAI demonstrated the highest predictive performance with an AUC value of 0.534, while in females, ABSI and HI exhibited superior predictive

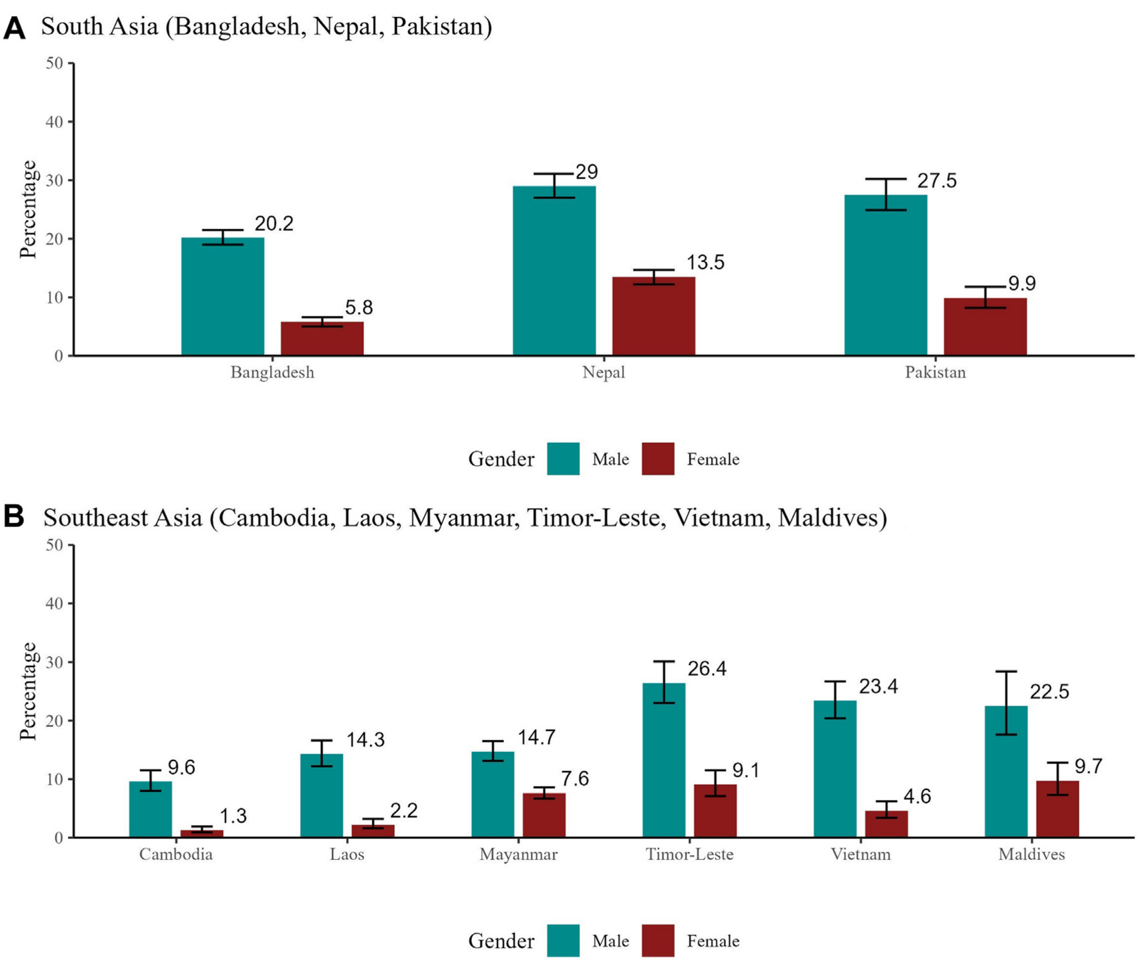

Fig. 2: **Prevalence of 10-year CVD-R ≥10% by sex and country based on WHO CVD non-laboratory-based charts in south Asia (a) and southeast Asia (b).**

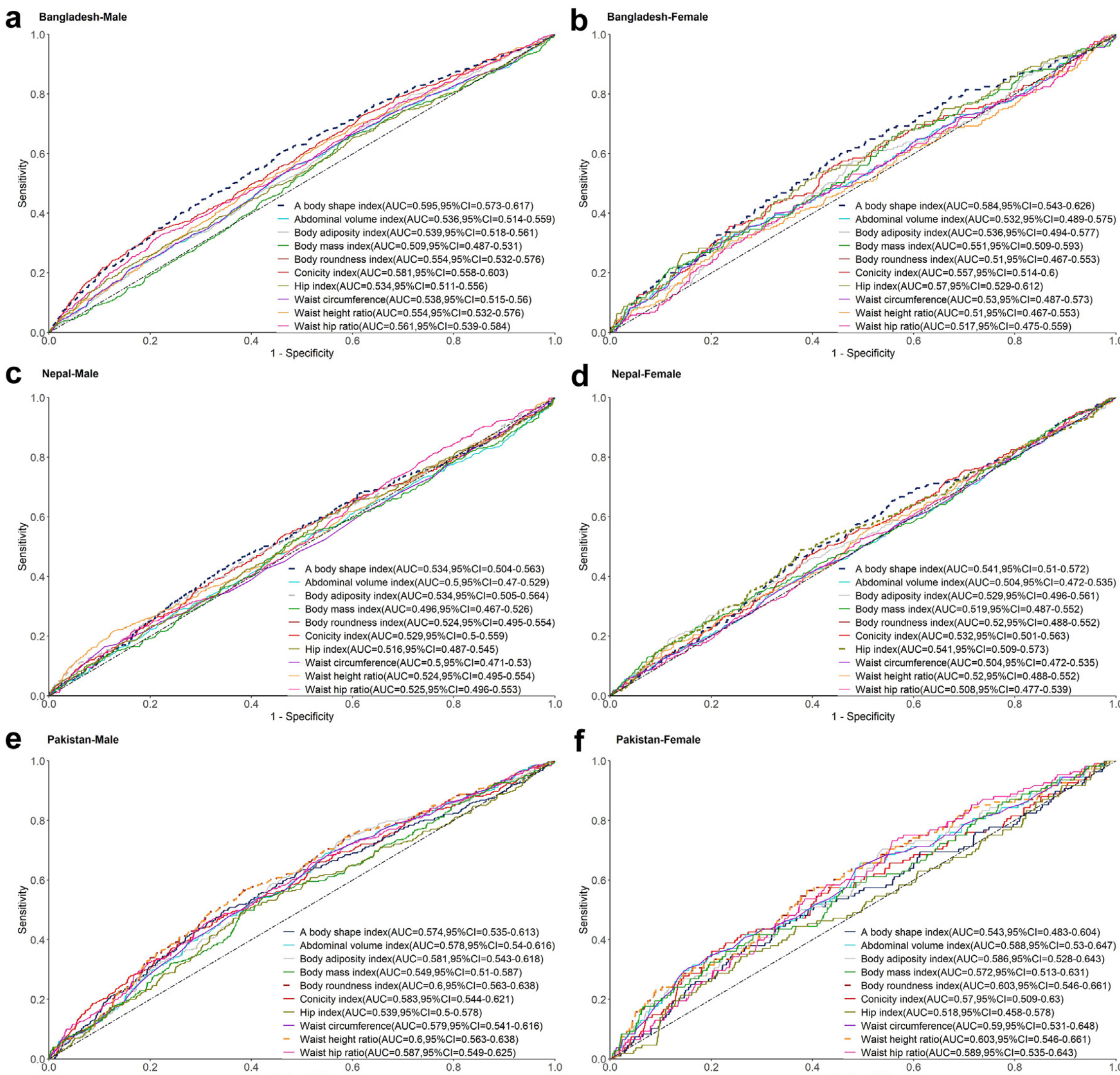

***Fig. 3:* ROC curves representing the predictive accuracy of anthropometric indices for 10-year CVD-R ≥ 10% using WHO-CVD-NL-C. The graphs (a) and (b) represent the outcomes for Bangladeshi males and females, whereas graphs (c), (d), (e), and (f) represent identical outcomes for Nepal and Pakistan, respectively. 10-year CVD-R ≥ 10%; 10-year CVD risk ≥ 10% WHO-CVD-NL-C; WHO CVD risk non-laboratory-based charts. Line pattern '—' indicates best-performing anthropometric index**.

accuracy with an AUC of 0.541 compared to other anthropometric indices. Among Nepalese males, BMI had the lowest predictive capacity with an AUC value of 0.496. The WHtR and BRI (AUC = 0.6) among Pakistani males displayed the best predictive performance. WHtR and BRI also outperformed other anthropometric indices in Pakistani females, demonstrating superior predictive accuracy with an AUC of 0.603.

Figs. 4 and 5 depict the predictive performance of ten anthropometric indices among males and females in southeast Asian countries (Cambodia, Laos, Myanmar, Timor-Leste, Vietnam, and the Maldives) based on ROC curve analysis in relation to WHO-CVD-NL-C. CI demonstrated a greater predictive accuracy among Cambodian males (AUC = 0.666) and females (AUC = 0.685) in predicting 10-year CVD-R ≥ 10%. Among males of Laos and Myanmar, the predictive power of BRI and WHtR surpassed that of other anthropometric indices in estimating 10-year CVD-R ≥ 10%. The AUC for both BRI and WHtR among the males of Laos was 0.662. Among males of Myanmar, the AUC for both BRI and WHtR was 0.654. Conversely, among females of Laos and Myanmar, ABSI exhibited superior performance in estimating 10-year CVD-R ≥ 10%, and the AUC were 0.639 and 0.594, respectively. Among males and females of Timor-Leste, ABSI exhibited

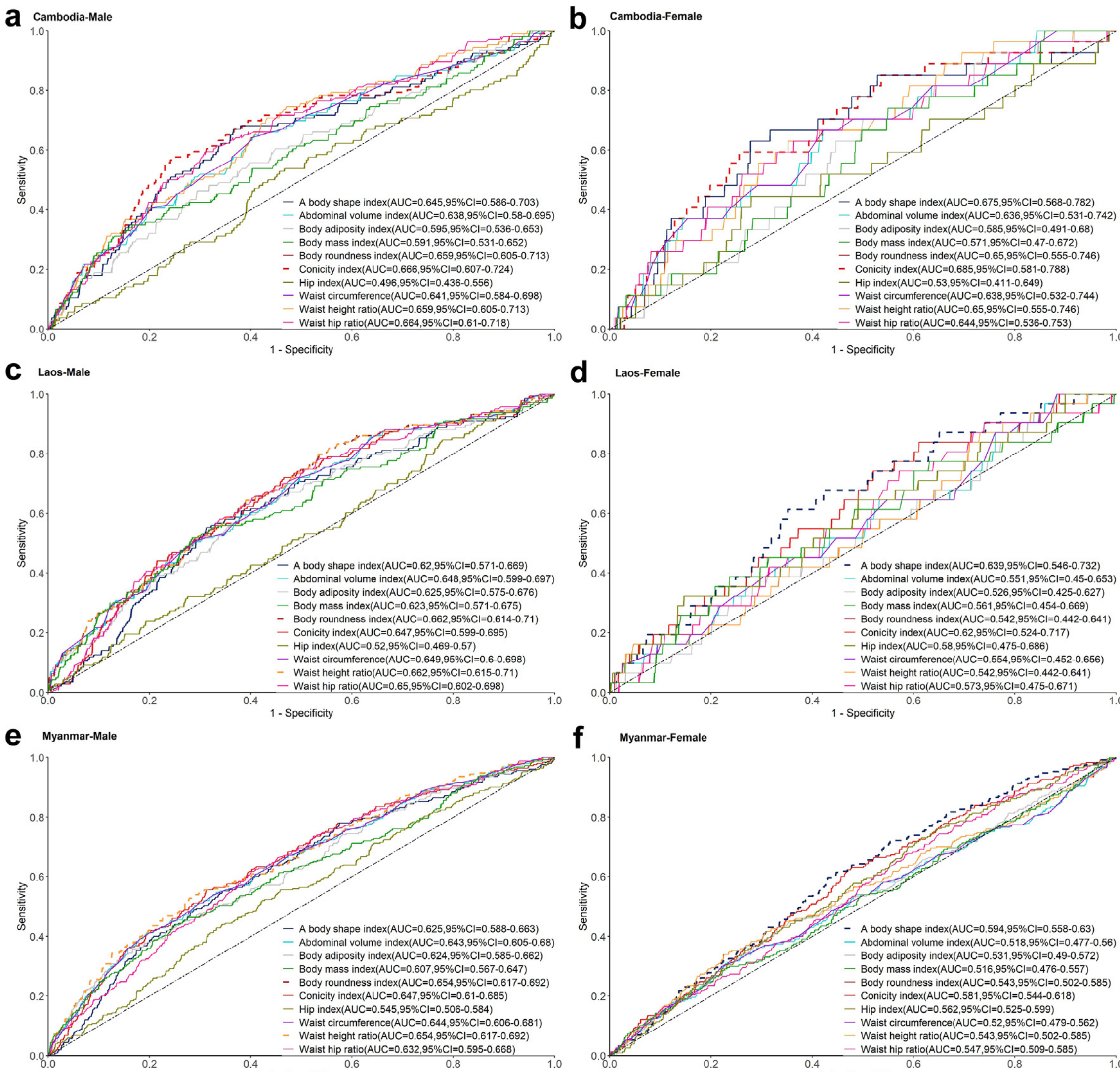

Fig. 4: **ROC curves representing the predictive accuracy of anthropometric indices for 10-year CVD-R ≥ 10% using WHO-CVD-NL-C. The graphs (a) and (b) represent the outcomes for Cambodian males and females, whereas the (c), (d), (e), and (f) represent identical outcomes for Laos and Myanmar, respectively. 10-year CVD-R ≥ 10%; 10-year CVD risk ≥10% WHO-CVD-NL-C; WHO CVD risk non-laboratory-based charts. Line pattern '—' indicates best-performing anthropometric index.**

superior predictive accuracy, with AUC values of 0.548 and 0.628, respectively. Among Timorese males, AVI had the lowest predictive capacity with an AUC value of 0.497. Within the Vietnamese male population, BRI and WHtR demonstrated the highest predictive accuracy (AUC = 0.629), while among females, CI exhibited superior predictive accuracy (AUC = 0.722). Further, among Maldivian males, WHR displayed the highest predictive accuracy (AUC = 0.687), whereas in females, CI showed superior predictive accuracy (AUC = 0.595).

Supplementary Table S6a outlines optimal cut-offs, sensitivity, specificity, and the Youden index of the best-performing anthropometric index for predicting 10-year CVD-R ≥ 10% using WHO-CVD-NL-C. Maldivian males showed the highest Youden index for WHR (0.32), while Cambodian females exhibited the highest Youden index for the conicity index (0.33). Supplementary Table S6a also reports significant differences in AUC between the best anthropometric index and other indices based on the DeLong method. Among Bangladeshi males, the AUC of the best-performing anthropometric index (ABSI) differed from that of the other nine indices ($p < 0.05$). For Pakistani males, Cambodian males, Burmese males and females, Timorese females, and Vietnamese females, the AUCs of the best-performing anthropometric indices differed from

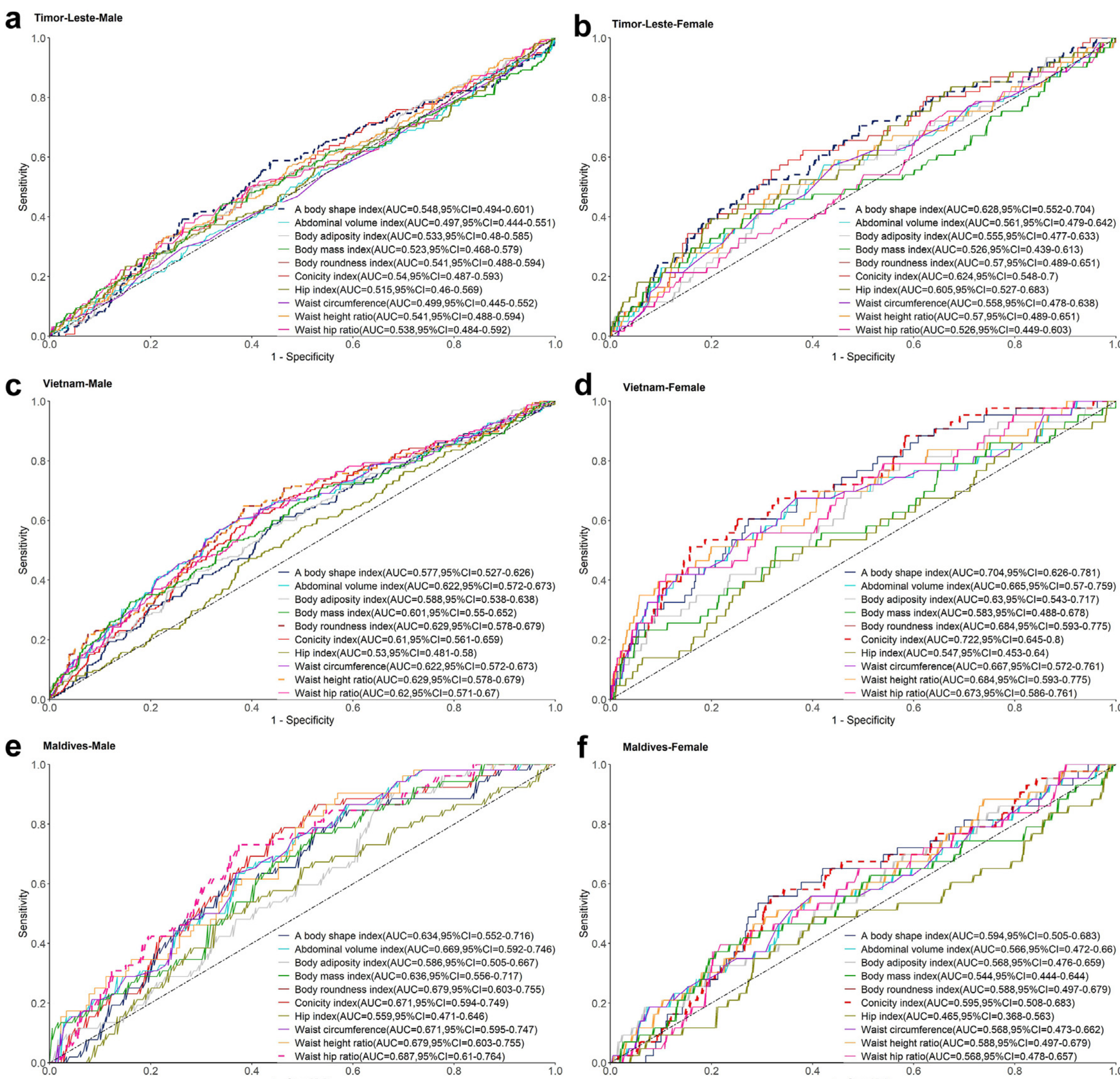

Fig. 5: **ROC curves representing predictive accuracy of anthropometric indices for 10-year CVD-R ≥ 10% using WHO-CVD-NL-C. The graphs (a) and (b) represent the outcomes for Timorese males and females, and (c), (d), (e), and (f) represent identical outcomes for Vietnam and Maldives, respectively. 10-year CVD-R ≥ 10%; 10-year CVD risk ≥10% WHO-CVD-NL-C; WHO CVD risk non-laboratory-based charts. Line pattern '—' indicates best-performing anthropometric index.**

the AUCs of BMI (p < 0.05). No statistically significant differences were observed between the AUC of the best-performing anthropometric index and other indices for Nepalese females, Cambodian females, Lao females, Timorese males, and Maldivian females. Similar analyses were done for best-performing anthropometric indices for predicting 10-year CVD-R ≥ 10% using WHO-CVD-L-C and reported in Supplementary Table S6b.

Association between best-performing anthropometric indices and 10-year CVD-R ≥ 10%

As depicted in Table 2, the study analysed the associations between best-performing anthropometric indices and 10-year CVD-R ≥ 10% (based on the analytic sample constructed for WHO-CVD-NL-C). Model 3, a multivariable-adjusted model, considered potential confounders like age, education, occupation, smoking history, physical activity, diet, and alcohol consumption. This model revealed statistically significant (p < 0.05) associations between the best-performing anthropometric indices and 10-year CVD-R ≥ 10% in Bangladesh (males), Pakistan (both sexes), Cambodia (both sexes), Laos (both sexes), Myanmar (males), Timor-Leste (females), and Vietnam (both sexes). Interestingly, in Nepalese males, two anthropometric indices (ABSI and BAI) performed best, but only BAI remained

Male				Female			
	Model—1: OR (95% CI)	Model—2: OR (95% CI)	Model—3[b]: OR (95% CI)		Model—1: OR (95% CI)	Model—2: OR (95% CI)	Model—3[b]: OR (95% CI)
South Asia							
Bangladesh							
ABSI	1.46 (1.32–1.61)[a]	1.15 (1.01–1.31)[a]	1.16 (1.009–1.35)[a]	ABSI	1.29 (1.14–1.45)[a]	1.08 (0.92–1.28)	1.09 (0.92–1.21)
Nepal							
ABSI	1.09 (0.98–1.21)	0.89 (0.77–1.11)	0.87 (0.75–1.01)	ABSI	1.14 (1.03–1.27)[a]	1.03 (0.91–1.17)	1.03 (0.88–1.19)
BAI	1.21 (1.06–1.36)[a]	1.34 (1.12–1.61)[a]	1.24 (1.01–1.52)[a]	HI	1.09 (0.98–1.21)	1.09 (0.96–1.22)	1.09 (0.94–1.26)
Pakistan							
BRI	1.45 (1.22–1.71)[a]	2.19 (1.66–2.89)[a]	2.24 (1.66–3.04)[a]	BRI	1.32 (1.12–1.55)[a]	1.75 (1.41–2.17)[a]	1.88 (1.46–2.43)[a]
WHtR	1.46 (1.24–1.71)[a]	2.24 (1.72–2.91)[a]	2.36 (1.78–3.14)[a]	WHtR	1.39 (1.15–1.66)[a]	1.84 (1.43–2.36)[a]	2.01 (1.49–2.67)[a]
Southeast Asia							
Cambodia							
CI	1.81 (1.43–2.28)[a]	1.64 (1.25–2.16)[a]	1.62 (1.21–2.17)[a]	CI	1.66 (1.21–2.28)[a]	1.43 (1.02–2.02)[a]	1.4 (1.01–2.07)[a]
Laos							
BRI	1.88 (1.52–2.33)[a]	1.85 (1.45–2.36)[a]	1.99 (1.54–2.59)[a]	ABSI	2.11 (1.31–3.39)[a]	1.62 (1.03–2.56)[a]	1.82 (1.08–3.05)[a]
WHtR	1.87 (1.47–2.39)[a]	1.81 (1.38–2.33)[a]	1.92 (1.46–2.53)[a]	–	–	–	–
Myanmar							
BRI	1.89 (1.56–2.28)[a]	1.81 (1.48–2.21)[a]	2.04 (1.64–2.55)[a]	ABSI	1.17 (1.05–1.31)[a]	1.02 (0.91–1.16)	1.004 (0.87–1.14)
WHtR	1.75 (1.51–2.03)[a]	1.69 (1.42–2.01)[a]	1.85 (1.54–2.24)[a]	–	–	–	–
Timor-Leste							
ABSI	1.02 (0.84–1.24)	1.03 (0.77–1.37)	0.88 (0.63–1.23)	ABSI	1.61 (1.23–2.07)[a]	1.51 (1.13–2.03)[a]	1.59 (1.11–2.26)[a]
Vietnam							
BRI	1.72 (1.41–2.12)[a]	1.78 (1.37–2.31)[a]	1.89 (1.42–2.53)[a]	CI	2.01 (1.52–2.65)[a]	1.76 (1.25–2.48)[a]	1.81 (1.25–2.58)[a]
WHtR	1.69 (1.39–2.06)[a]	1.74 (1.36–2.23)[a]	1.85 (1.41–2.43)[a]	–	–	–	–
Maldives							
WHR	1.21 (0.94–1.55)	1.22 (0.89–1.67)	1.19 (0.88–1.61)	CI	1.46 (0.98–2.17)	0.94 (0.63–1.41)	0.81 (0.41–1.55)

Abbreviations: ABSI, a body shape index; BAI, body adiposity index; BRI, Body roundness index; CI, conicity index; HI, Hip index; WHtR, waist-to-height ratio; WHR, waist-to-hip ratio; OR, odds ratio. Note: associations were observed only for the anthropometric indices that demonstrated the highest AUC in the ROC curve analyses. [a]Indicates statistical significance ($p < 0.05$).Model–1: Non-adjusted.Model–2: Adjusted for age.Model–3: Adjusted for age, years of education, occupation, history of smoking (present smoker, past smoker and non-smoker), physical activity (sufficient physical activity and insufficient physical activity, participants who participated in less than the equivalent of 150 min of moderate-intensity (600METs) physical activity per week), dietary pattern (sufficient fruit and vegetable intake and insufficient fruit and vegetable intake (refers to those who ate less than five servings of fruits vegetables per day), and consumption of alcohol in last thirty days. [b]The choice of variables in Model 3 was depended on the data availability and it varied across the countries being studied. In the analyses of Bangladesh, Pakistan and Maldives consumption of alcohol were not included in the Model 3. In the analysis of Vietnam occupation was not included in the Model 3.

Table 2: **Logistic regression analyses (by country and sex) to determine the association between 10-year CVD-R ≥ 10% (based on the analytic sample constructed for WHO-CVD-NL-C) and anthropometric indices (z-score) which were performed best in the ROC curve analyses.**

significantly ($p = 0.03$) associated with 10-year CVD-R ≥ 10% after adjusting for confounders. Notably, after adjusting for confounders, no significant association was found between the best-performing index and 10-year CVD-R ≥ 10% in Bangladesh (females), Nepal (females), Myanmar (females), Timor-Leste (males), and Maldives (both sexes). Similar analyses were done for the best-performing anthropometric indices for predicting 10-year CVD-R ≥ 10% using WHO-CVD-L-C and these are reported in Supplemental Table S7.

Discussion

Anthropometric indices predict CVD risk with varying effectiveness across south and southeast Asian populations. ABSI, BAI, and WHtR were optimal predictors for 10-year CVD-R ≥ 10% in south Asian males, while ABSI and WHtR stood out for south Asian females. In Nepalese males, BMI failed (AUC <0.5) in identifying 10-year CVD-R ≥ 10%. Among southeast Asian males, CI, ABSI, WHtR, and WHR excel. Conversely, in Timorese males, WC and AVI were ineffective (AUC <0.5), while in southeast Asian females ABSI and CI performed best in identifying 10-year CVD-R ≥ 10%.

A study from India supported the WHtR's superior predictive accuracy for CVD risk factors over BMI, such as insulin resistance.[11] Study results for Bangladesh and Nepal also supported these findings, showing WHtR consistently outperforming BMI and WC but falling short against ABSI and CI. In India, novel indices like BAI, BRI, AVI, ABSI, and CI demonstrated superiority in predicting CVD risk factors.[12] Pakistani samples also favour WHtR, consistent with recent findings.[13,14] Prior research conducted in southeast Asian nations, including Thailand, Singapore, and Malaysia, WHtR or waist-related measurements have proven to be a more effective predictor of CVD and its risk factors when compared to BMI.[15–17] However, these studies do not incorporate newly developed anthropometric indices such as BAI, BRI, ABSI, AVI, and CI. A recent systematic review and meta-analysis of 31 studies showed WHtR to be significantly better than BMI and WC for predicting diabetes, hypertension, and CVD in males and females. The limitations of this systematic review also include not examining the performance of recently developed indices.[3] In our study, among the southeast Asian population, WHtR had superior predictive performance, particularly among males of Laos, Myanmar, and Vietnam, and outperformed all novel anthropometric indices. However, in most cases, the ABSI or CI consistently demonstrated the highest AUC compared to all other anthropometric indices in the southeast Asian population. WHR demonstrated the best predictive performance only among males of the Maldives. In this study, WHtR and BRI demonstrated comparable results with negligible variation, consistent with the findings of prior research.[18]

A higher ABSI value signifies an increased WC relative to the expected values for a given height and weight, indicating greater abdominal fat deposition, which is associated with inflammatory processes, insulin resistance, and skeletal muscle loss leading to abdominal obesity. Notably, ABSI independently predicts the occurrence of CVD and mortality, distinct from BMI.[19] Like a study from China,[7] this study illustrated that ABSI was the best anthropometric index for estimating 10-year CVD risk in Bangladeshi males and females and in Nepalese females. A study in India also found a strong association between ABSI and CVD risk factors.[20] Conversely, a study in the Netherlands found that ABSI did not perform better in detecting CVD compared to BRI, BMI, and WC.[19] ABSI has been suggested to potentially overestimate the risk of CVD, considering its linear relationship with age.[21] A meta-analysis revealed that for each standard deviation increase in ABSI, there were 13% higher odds of hypertension, 35% higher odds of type 2 diabetes, 21% higher risk of CVD, and a substantial 55% higher risk of all-cause mortality.[22] While ABSI performed better than BMI and WC in predicting overall mortality, it demonstrated lower accuracy in predicting chronic diseases. Furthermore, ABSI is tightly clustered around the mean with minimal variance, posing challenges in establishing a clear clinical cut-off for practical use.[22]

The CI is a measure of abdominal obesity created through geometric reasoning. It has demonstrated higher sensitivity and effectiveness compared to the WHR in indicating the risk of hyperlipidaemia in Western populations.[23] Recent findings from Iran revealed that the performance of CVD risk prediction was most notable with the use of CI, particularly in forecasting 7- and 10-year CVD risks. Conversely, studies conducted in China demonstrated suboptimal CI performance in relation to CVD risk factor prediction.[24] On the other hand, one study from China was able to demonstrate that CI had a better ability to predict all-cause mortality among cancer-free older people.[25]

The BRI emerges as a novel metric for evaluating body composition and potential CVD risk. This index transcends weight-centric approaches by incorporating height and waist circumference to quantify body shape sphericity. A lower BRI (closer to 1) signifies an elliptical (less round) body shape, potentially associated with reduced body fat. Conversely, a higher BRI (up to 16) reflects a more circular body form. Investigations suggest BRI may outperform established methods such as BMI and WC in identifying CVD and CVD risk factors. Studies also demonstrated a stronger association between BRI and CVD risk factors compared to traditional measurements.[12,19]

Variations in the performance of anthropometric indices in predicting CVD or CVD risk factors might be attributed to ethnic, racial, and lifestyle differences and different diagnostic cut-offs for CVD risk factors.[12] Studies suggest that ethnicity-related genetic heritage can have an impact on abdominal and hepatic fat accumulation, insulin secretion and sensitivity, as well as the quality and quantity of circulating lipid particles affecting the risk of CVD morbidity.[26] Moreover, lipid metabolism and the locality of body fat accumulation are largely influenced by genetic and hormonal factors, with estrogen displaying a protective function both in terms of favourable fat deposition and insulin sensitivity.[27] Oestrogen promotes the release of nitric oxide and exerts an anti-inflammatory effect, protecting from free radical damage by regulating uric acid levels, providing a benefit to pre-menopausal females. It also takes part in insulin release regulation, which, in turn, has a significant role in lipid metabolism and vascular regulation.[28] The pathophysiology of abdominal obesity, insulin resistance, and CVD risk, particularly considering gender and ethnicity, is illustrated in Supplementary Figure S3.

The performance of anthropometric indices may vary between hypertension and diabetes within the same population. For instance, in a study from India, the BRI exhibited the highest predictive accuracy for diabetes among males, whereas the BAI illustrated superior performance in predicting hypertension in the same population and CI performed better in predicting high triglyceride in comparison to BAI and BRI.[12] Differences may arise in studies examining the association between anthropometric indices and various methods for identifying CVD risk, such as the Framingham CVD Risk Score, European SCORE, and the American College of Cardiology/American Heart Association (ACC/AHA) equation. In a Spanish study, WHtR proved optimal for predicting high CVD risk using Framingham and ACC/AHA scores, while ABSI excelled for the European SCORE.[29] The current study also noted variations and similarities between WHO-CVD-NL-C and WHO-CVD-

L-C in assessing the performance of anthropometric indices. Though there are some variations, the anthropometric index has been identified as best-performing compared with WHO-CVD-NL-C also outperforming WHO-CVD-L-C (Supplemental Figures S4, S5, and S6). It is imperative to note that AUC values between 0.5 and 0.6 suggest limited diagnostic performance, indicating a moderate ability to distinguish between individuals with 10-year CVD-R ≥ 10%. The highest Youden index reported was 0.33 for Maldivian females, indicating moderate diagnostic performance with 74% sensitivity and 59% specificity. Primarily this study evaluated the performance of anthropometric indices using the WHO-CVD- NL-C, which does not incorporate participants' cholesterol levels and diabetes status, potentially underestimating CVD risk. However, when using the WHO-CVD- L-C tool, which includes these factors, we observed higher performance metrics, with AUCs exceeding 0.7 in Cambodian and Vietnamese females and the Youden index crossing 0.45 (64% sensitivity and 81% specificity) in Cambodian females. This suggests that the inclusion of more comprehensive health information improves predictive power. From a public health perspective, even though the AUC and Youden index scores utilising WHO-CVD-NL-C are mild to moderately strong, they are still useful for CVD risk screening, especially in low-resource settings.

It is essential to note that the highest-performing anthropometric index for identifying CVD risk based on the AUC value of ROC analysis does not necessarily imply an independent association between the highest-performing anthropometric index and CVD risk. Despite identifying the best-performing index based on the highest AUC for some countries, we found no significant association between the z-score of the highest-performing anthropometric index and CVD risk in our logistic regression analysis. Confounding factors, sample size, study design, sub-group analyses in different age groups, and non-linear relationships can further obscure the true relationship between the highest-performing anthropometric index and CVD risk. Further examining performance in total males and total females across south Asia and southeast Asia could be beneficial for practical applicability in clinical settings. Because of the absence of data from India and Bhutan (which constitute a significant portion of south Asia) and from Thailand, Malaysia, Philippines, and Indonesia (key countries in southeast Asia), we decided to focus on country-specific results rather than regional ones.

The study's strengths include a large, standardised, and high-quality dataset, enabling a comprehensive comparison of traditional and new anthropometric indices in south and southeast Asian populations. Limitations include the cross-sectional design, precluding causal inferences. Moreover, the performance of anthropometric indices was only tested against the moderate CVD risk group because of the inadequate sample size in the high-risk group (CVD-R ≥ 20%). This study confirms that the association between anthropometric indices and CVD risk differs across south Asian and southeast Asian populations. Our study also suggests that BMI, a frequently utilised metric in predicting CVD within south and southeast Asian nations, may not be the most dependable predictor in this context. The American Medical Association has already recognised the limitations of BMI as a body fat measure and has advocated for alternative methods to diagnose obesity.[30] south Asian and southeast Asian countries should incorporate the best-performing anthropometric index in primary care settings and population-based health screening. This practice is essential for assessing future CVD risk and designing appropriate interventions. However, validation through prospective studies is necessary, and future research in similar settings should also test the performance of the anthropometric indices in high-risk group and explore the identified cut-offs' associations with cardiovascular and all-cause mortality in these populations.

This study tried to unravel potential variations in the predictive strength of anthropometric indices for 10-year cardiovascular risk in south and southeast Asian populations. Our study revealed a geographically diverse picture of how anthropometric indices predict CVD risk. In south Asia, ABSI, BAI, BRI, HI, and WHtR seem to be more credible anthropometric indices, while ABSI, CI, BRI, WHR, and WHtR hold greater significance for southeast Asians to predict CVD risk. While identifying the best-performing anthropometric index based on AUC values is informative, it is crucial to recognise that this does not always indicate a significant independent association with CVD risk. Such insights could aid in the identification of individuals at higher risk and enable more precise risk stratification and intervention planning.

Contributors
MTI: conceptualisation, data curation, formal analysis, investigation, methodology, software, visualisation, writing—original draft, and writing—review & editing, ATC: data curation and writing–review & editing, MSS: visualisation and writing–review and editing, AYMA: writing–review and editing, TM: writing–review and editing, MT: writing–review and editing, MRT: conceptualisation, supervision, validation, visualisation, and writing– review & editing, SMR: conceptualisation, supervision, validation, and writing– review & editing. MRT and SMR equally contributed as senior authors.

Data sharing statement
The analysis dataset for this specific manuscript is available from the corresponding author upon reasonable request. Data used in this study are available for the public at the website of WHO's NCD Microdata Repository (https://extranet.who.int/ncdsmicrodata/index.php/home#:~:text=The%20WHO%20NCD%20microdata%20repository,for%20NCD%20prevention%20and%20control). Data can be downloaded by following the instructions.

Declaration of interests
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Appendix A. Supplementary data
Supplementary data related to this article can be found at https://doi.org/10.1016/j.lansea.2024.100481.

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