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ORIGINAL RESEARCH

Correlation Between Anthropometric Measurements with Cardiometabolic Biomarkers and Ten-Year Cardiovascular Risk Score Among People with HIV in Uganda

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Background: Cardiometabolic diseases, including hypertension, dyslipidemia, diabetes, and obesity, increase the risk of cardiovascular disease (CVD) among people with HIV (PWH). Anthropometric measurements are widely used to estimate cardiometabolic risk, but their correlation with specific cardiometabolic biomarkers and cardiovascular risk in PWH remains unclear.

Methods: A cross-sectional study was conducted among PWH receiving care at Kiruddu National Referral Hospital in Uganda. Anthropometric measurements included body mass index (BMI), weight, mid-upper arm circumference (MUAC), waist circumference (WC), hip circumference (HC), neck circumference (NC), waist-to-height ratio (WHtR), and waist-to-hip ratio (WHR). Cardiometabolic parameters assessed included blood pressure (BP), glycated hemoglobin, fasting blood glucose (FBG), total cholesterol, LDL-C, HDL-C, triglycerides, serum uric acid, and the 10-year CVD risk score based on the Framingham Risk Score (FRS). Correlations were assessed using Pearson's correlation coefficients and Point-Biserial correlation (r).

Results: Among 396 PWH, anthropometric measurements were strongly intercorrelated. MUAC exhibited strong correlations with weight (r=0.84), BMI (r=0.81), HC (r=0.71), and WC (r=0.72) (all p<0.001). WC was strongly correlated with WHtR (r=0.93), weight (r=0.82), and BMI (r=0.78) (all p<0.001). However, correlations between anthropometric measurements and cardiometabolic biomarkers were weak. WC showed the strongest positive correlations with systolic BP (r=0.34), diastolic BP (r=0.31), total cholesterol (r=0.28), LDL-c (r=0.25), serum uric acid (r=0.25), triglycerides (r=0.22), and FBG (r=0.14). Similarly, correlations with the FRS were weak, whereby NC (r=0.37), weight (r=0.24), and WC (r=0.23) showed the strongest positive correlation, while other anthropometric indices had weak or negligible correlations with FRS.

Conclusion: Anthropometric measurements were strongly intercorrelated but demonstrated poor correlations with cardiometabolic biomarkers and the 10-year FRS among PWH in Uganda. These findings suggest that while anthropometric indices remain practical for initial screening, they may not reliably predict cardiometabolic risk or long-term CVD risk, highlighting the need for more comprehensive assessment tools in PWH.

Keywords: HIV, BMI, obesity, risk score, diabetes, hypertension, anthropometry

Introduction

Cardiometabolic diseases, including hypertension, dyslipidemia, diabetes, and obesity, are emerging as significant health concerns among people living with HIV (PWH), particularly in sub-Saharan Africa (SSA).[1] These conditions are of critical concern because they substantially increase the risk of cardiovascular disease (CVD), which is now recognized as

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a leading cause of morbidity and mortality in PWH.[2] CVD in PWH is driven by chronic inflammation, endothelial dysfunction, and metabolic alterations—including those associated with antiretroviral therapy.[3] The risk of atherosclerotic CVD in PWH is estimated to be twice that of the general population, underscoring the urgency of addressing CVD risk factors in this group.[4] Accurate risk stratification and early detection of cardiometabolic diseases are, therefore, essential for mitigating the burden of CVD in PWH. Abnormal body fat distribution, such as central adiposity and lipoatrophy, is common in HIV and strongly correlates with insulin resistance, dyslipidemia, and increased CVD risk, making anthropometric assessment a key tool in routine cardiovascular risk stratification.[5]

Anthropometric measurements, such as weight, body mass index (BMI), waist circumference (WC), mid-upper arm circumference (MUAC), hip circumference (HC), neck circumference (NC), waist-hip ratio (WHR), and waist-to-height ratio (WHtR), are widely employed in clinical practice and epidemiological studies to assess cardiometabolic risk.[6] These indices are cost-effective, non-invasive, and easy to obtain, making them particularly valuable for resource-limited settings where access to advanced diagnostic tools may be limited. Current clinical guidelines recommend periodic measurement of anthropometric indices alongside blood pressure, fasting lipids, and glucose levels to assess CVD risk in PWH.[7] However, in SSA, anthropometric measurements are often the only readily available screening tool, as access to laboratory-based cardiometabolic testing remains limited.[8] Despite their practicality, the accuracy of anthropometric indices in predicting cardiometabolic disease risk is relatively low in HIV-negative people, particularly in SSA.[9,10]

In PWH, evidence from studies conducted outside SSA suggests that anthropometric measures such as WC, BMI, and WHtR strongly correlate with key predictors of CVD risk, including metabolic syndrome, lipid abnormalities, and insulin resistance.[11–14] These anthropometric measures have been proposed as potential surrogates for assessing cardiometabolic risk. However, there is insufficient evidence from SSA to delineate the utility of anthropometric indices for this purpose. The prevalence of cardiometabolic risk factors among PWH in Uganda is alarmingly high. Studies estimate that dyslipidemia affects 32–94% of PWH, hyperglycemia occurs in 18–45%, hypertension affects 8–32%, and hyperuricemia is present in up to 39% of PWH.[15–18] Projections indicate that approximately 41,000 PWH in Uganda may experience a CVD event between 2016 and 2025, with 38% of these events expected to be fatal.[19] Given this, understanding how anthropometric measurements correlate with cardiometabolic biomarkers and CVD risk is critical, as these measurements remain the most accessible screening tool for CVD risk in resource-constrained settings like Uganda. This study aimed to evaluate the correlations between anthropometric measurements and cardiometabolic biomarkers, as well as the 10-year CVD risk score based on the Framingham Risk Score (FRS), among PWH receiving care at a tertiary hospital in Uganda. We hypothesized that there will be strong correlations between the anthropometric measurements and the biomarkers, as well as the FRS.

Materials and Methods

Study Design, Site and Population

This was a secondary analysis of data from a cross-sectional study[20] conducted at Kiruddu National Referral Hospital (KNRH) in Kampala, the capital city of Uganda. The primary study's aim was to determine the association between prior tuberculosis infection with cardiometabolic risk factors. In the current analysis, we included adult PWH (aged ≥18 years) who were enrolled in the previous study and who had at least one anthropometric measurement and measurements for any of the following: blood pressure (BP), lipid profile, glycated hemoglobin (HbA1c), fasting blood glucose (FBG) and serum uric acid levels.

Study Measurements

A structured questionnaire was administered to collect information on participants' socio-demographic and clinical characteristics, history of cigarette smoking, alcohol use, and family history of CVD risk factors. Cigarette smoking was quantified in pack-years, while alcohol use was assessed using the CAGE questionnaire, with a score of ≥2 indicating hazardous alcohol consumption.[21] The CAGE questionnaire comprises four questions: "Have you ever: (1) felt the need to Cut down your drinking; (2) felt Annoyed by criticism of your drinking; (3) felt Guilty about drinking; and (4) needed a morning Eye-opener?" HIV treatment-related data, including ART regimens, viral load suppression status, history of opportunistic infections, and CD4 cell counts, were retrieved from the HIV treatment database at KNRH.

Anthropometric measurements, including weight, height, MUAC, NC, WC, and HC, were taken using standardized tools: a weighing scale (Seca 760®), a stadiometer (Seca 213®), and a tape measure. BMI was calculated as weight (in kilograms (kg)) divided by height squared (m^2). Blood pressure (BP) was measured using a digital BP machine (Omron®, Hem 7120) on two occasions, 20 minutes apart, and the average value was recorded as the participant's BP. Blood samples were analyzed for fasting blood glucose (FBG), glycated hemoglobin (HbA1c), serum uric acid, and fasting lipid profiles. FBG was measured using a point-of-care glucometer (Accu-Chek®), while serum uric acid levels and lipid parameters, including triglycerides, total cholesterol, low-density lipoprotein cholesterol (LDL-c), and high-density lipoprotein cholesterol (HDL-c), were assessed using the Cobas® 6000 analyzer series (Roche Diagnostics, USA).

Study Outcomes

The primary outcomes of the study were the intercorrelation coefficients among individual anthropometric measurements and the correlation coefficients between these measurements and cardiometabolic biomarkers, as well as the 10-year CVD risk score based on the Framingham model.[22] Anthropometric measurements included weight, BMI, MUAC, NC, WC, HC, WHR, and WHtR. Cardiometabolic biomarkers assessed were FBG, HbA1c, systolic and diastolic BP, total cholesterol, LDL-c, HDL-c, triglycerides, and serum uric acid. Derived cardiometabolic risk factors included hypertension, dyslipidemia, elevated FBG, and diabetes mellitus (DM). Hypertension was defined as systolic BP ≥140 mmHg, diastolic BP ≥90 mmHg, or the use of antihypertensive medications.[23] Dyslipidemia was characterized by elevated total cholesterol (>5.0 mmol/l), elevated LDL-c (>4.14 mmol/l), elevated triglycerides (≥1.7 mmol/l), or low HDL-c (<1.03 mmol/l in men and <1.29 mmol/l in women).[24] Elevated FBG was defined as FBG ≥5.6 mmol/l, while HbA1c ≥5.7% was considered elevated. DM was defined as FBG ≥7.0 mmol/l, HbA1c ≥6.5%, or the use of antihyperglycemic agents.[25] The 10-year CVD risk score was calculated using the Framingham Risk Score (FRS), incorporating factors such as age, sex, lipid levels, BP, and smoking status.[22]

Sample Size Estimation

Considering a correlation coefficient (r) between the BMI and FRS of 0.1836,[26] a two-tailed alpha of 0.05 and a beta of 0.20, we estimate that a sample size of 240 would be sufficient. However, we conducted a census of the entire population from the primary study.

Statistical Analysis

Data were analyzed with Stata 18.0 (StataCorp LLC, College Station, USA). Descriptive statistics were used to summarize the socio-demographic and clinical characteristics of the study participants. Continuous variables were reported as means and standard deviations (SD) or medians with interquartile ranges (IQR), depending on their distribution. We tested for normality using the Shapiro–Wilk test. Categorical variables were summarized as frequencies and percentages. The primary analysis focused on the pairwise correlations between anthropometric measurements and their associations with cardiometabolic biomarkers and the 10-year FRS. Pearson's correlation coefficients (r) were calculated when comparing continuous variables while the Point-Biserial correlation was used when comparing continuous variables and a binary outcome (such as elevated lipids, BP, obesity, FBG). Intercorrelations between individual anthropometric measurements were assessed. Further, correlations between anthropometric measurements and cardiometabolic biomarkers were evaluated. Additionally, associations with derived cardiometabolic risk factors were assessed using the correlation coefficients.

The correlation between anthropometric measurements and the 10-year CVD risk score was also determined using Pearson's correlation coefficients. For all analyses, a two-tailed p-value of less than 0.05 was considered statistically significant.

Results

Characteristics of Participants

A total of 396 PWH were included in the study. The mean age of the participants was 41.5 years (standard deviation, SD: 12.2). Males were 185 (46.7%), and participants had been on ART for a median (IQR) of 4.0 (1.7–10.0) years. Viral load suppression (<1000 copies per mL) had been achieved among 309 (94.8%). The prevalence of self-reported cardiometabolic diseases was: diabetes (6.3%), hypertension (16.7%), and dyslipidemia (0.3%). Other characteristics are shown in Table 1.

Table 1 Characteristics of Study Participants

Characteristic (N=396)	Frequency (%)
Male Sex	185 (46.7)
Tribe	
Baganda	253 (64.2)
Banyakitara	81 (20.6)
Others	60 (15.2)
Urban Residence	279 (70.5)
Duration at current residence (Months), Median (IQR)	7.0 (3.0–20.0)
Married	176 (44.4)
At least Secondary school education level	192 (48.5)
Unemployed	67 (16.9)
Currently on Trimethoprim/Sulfamethoxazole prophylaxis	100 (25.3)
Drugs in antiviral therapy (ART) Regimen	
Tenofovir	380 (96.0)
Lamivudine	392 (99.0)
Abacavir	6 (1.5)
Zidovudine	6 (1.5)
Efavirenz	21 (5.3)
Dolutegravir	365 (92.2)
Protease inhibitor (Lopinavir, Ritonavir, or Atazanavir)	13 (4.4)
Duration on ART (Years), Median (IQR)	4.0 (1.7–10.0)
History of ART default	40 (10.2)
CD4 count at HIV diagnosis, (cells/ μL), Median (IQR)	237.5 (97.5–471.0)
Clinical stage of HIV at time of HIV diagnosis	
Stage I	176 (44.4)
Stage II	38 (9.6)
Stage III/IV	182 (46.0)
At least one past opportunistic infection (except Lower Respiratory Tract Infection)	58 (14.6)
Alcohol use	
Never used alcohol	158 (40.1)
Formerly used alcohol (>6 months)	118 (29.9)
Currently uses alcohol (within past 6 months)	118 (29.9)

(*Continued*)

Table 1 (Continued).

Characteristic (N=396)	**Frequency (%)**
CAGE[#]	
0-1	372 (94.4)
2-4	22 (5.6)
Smoking	
Never smoked	314 (80.1)
Formerly smoked (>6 months)	51 (13.0)
Currently smokes (<within past 6 months)	27 (6.9)
Pack years of smoking, Median (IQR)	1.8 (0.8–3.2)
Any family history of cardiovascular disease in first degree relative[β]	177 (44.7)
Specific family history of cardiovascular disease in first degree relative	
Diabetes mellitus	82 (46.3)
Hypertension	132 (74.6)
Kidney disease	7 (4.0)
Stroke	13 (7.3)
Obesity	16 (9.0)
Heart failure	5 (2.8)

Notes: [#]Score for hazardous alcohol use (C- cut down, A – anger, G –guilt, E – eye opener), [β]Includes any of Diabetes mellitus, Hypertension, Kidney disease, Stroke, Obesity and Heart failure.

Intercorrelation of Anthropometric Measurements

WC exhibited strong positive correlations with waist-height ratio (r=0.93), weight (r=0.82), and BMI (r=0.78), all p<0.001. Similarly, MUAC showed a strong positive correlation with weight (r=0.84), BMI (r=0.81), hip circumference (r=0.71), and waist circumference (r = 0.72), all p<0.001. HC was also strongly correlated with BMI (r=0.75) and weight (r=0.76), p<0.001. The NC demonstrated the weakest intercorrelation with other anthropometric measurements. Other intercorrelations are shown in Table 2.

Table 2 Intercorrelation of Anthropometric Measurements Among PWH

Characteristic	**BMI (r)**	**Weight (r)**	**MUAC (r)**	**NC (r)**	**WHR (r)**	**HC (r)**	**WC (r)**
Weight	0.85*	1.00					
Mid upper arm circumference (MUAC)	0.81*	0.84*	1.00				
Neck circumference (NC)	0.31*	0.56*	0.39*	1.00			
Waist hip ratio (WHR)	0.11[a]	0.16	0.11[b]	0.21*	1.00		
Hip circumference (HC)	0.75*	0.76*	0.71*	0.27*	−0.31*	1.00	
Waist circumference (WC)	0.78*	0.82*	0.72*	0.40*	0.43*	0.69*	1.00
Waist Height ratio (WtHR)	0.84*	0.69*	0.68*	0.22*	0.39*	0.67*	0.93*

Notes: *Means p<0.01, [a]p= 0.028, [b]p =0.033, r- Pearson's correlation coefficient.

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Correlation of Anthropometric Measurements with Cardiometabolic Profiles

There was a poor correlation between all anthropometric measurements and cardiometabolic profiles (Table 3).

1. **Hypertension and Blood Pressure**: WC showed the strongest positive correlations with hypertension (r=0.30), systolic blood pressure (SBP; r=0.34), and diastolic blood pressure (DBP; r=0.31), all p<0.01.
2. **Lipid Parameters**: WC had the strongest positive correlations with total cholesterol (r=0.28) and LDL (r=0.25), p<0.01. Triglycerides were weakly positively correlated with WC (r=0.22), weight (r=0.16), and NC (r=0.14), p<0.001. There were no significant correlations for the HDL-c.
3. **Glycemic Parameters (FBG and HbA1c)**: WC had a very weak positive correlation with FBG (r=0.14; p=0.006). No significant correlations were observed with HbA1c.

Table 3 Correlation of Anthropometric Measurements with Cardiometabolic Profiles Among PWH

Characteristic	BMI r (p-value)	Weight r (p-value)	MUAC r (p-value)	NC r (p-value)	WHR r (p-value)	HC r (p-value)	WC r (p-value)	WHtR r (p-value)
Hypertension	0.20*	0.29*	0.21*	0.22*	0.15*	0.22*	0.30*	0.24*
Dyslipidemia	0.18*	0.17*	0.17*	0.04 (0.433)	0.06 (0.269)	0.15*)	0.18*	0.18*
Diabetes	0.03 (0.526)	0.02 (0.707)	−0.00 (0.935)	0.06 (0.235)	0.04 (0.402)	0.05 (0.287)	0.11 (0.037)	0.11 (0.037)
Serum Uric acid	0.15*	0.25 *	0.15*	0.26*	0.24*	0.05 (0.311)	0.25*	0.15*
Triglycerides	0.09 (0.075)	0.16*	0.09 (0.071)	0.14*	0.14*	0.09 (0.070)	0.22*	0.15*
SBP	0.22*	0.28*	0.22*	0.24*	0.19*	020*	0.34*	0.28*
DBP	0.21*	0.26*	0.17*	0.17*	0.15*	0.21*	0.31*	0.26*
HbA1c	0.09 (0.063)	0.10 (0.048)	0.04 (0.402)	0.03 (0.493)	0.01 (0.902)	0.08 (0.128)	0.10 (0.057)	0.07 (0.173)
FBG	0.02 (0.756)	0.07 (0.180)	0.04 (0.408)	0.07 (0.153)	0.10 (0.051)	0.06 (0.239)	0.14*	0.10 (0.048)
Total Cholesterol	0.22*	0.18*	0.17*	0.13 (0.013)	0.10 (0.044)	0.19*	0.28*	0.28*
HDL	−0.08 (0.112)	−0.09 (0.086)	−0. 80 (0.180)	−0.04 (0.480)	0.04 (0.423)	−0.06 (0.216)	−0.02 (0.692)	−0.02 (0.626)
LDL	0.22*	0.17*	0.15*	0.08 (0.111)	0.09 (0.080)	0.18*	0.25*	0.26*
Elevated FBG	−0.05 (0.359)	0.03 (0.594)	0.02 (0.735)	0.04 (0.451)	0.10 (0.057)	0.00 (0.964)	0.06 (0.208)	0.03 (0.621)
Central Obesity	0.42*	0.37*	0.36*	0.16*	0.56*	0.21*	0.60*	0.61*
Obesity (using BMI)	0.77*	0.66*	0.61*	0.23*	0.05 (0.325)	0.63*	0.63*	0.68*
High BMI	0.80*	0.71*	0.67*	0.27*	0.12 (0.017)	0.63*	0.67*	0.70*
Elevated BP	0.12 (0.019)	0.20*	0.12 (0.018)	0.16*	0.11 (0.035)	0.15*	0.23*	0.16*
Elevated HBA1c	0.06 (0.228)	0.09 (0.074)	0.06 (0.257)	0.07 (0.194)	−0.06 (0.267)	0.11 (0.026)	0.06 (0.264)	0.03 (0.615)
Elevated Cholesterol	0.19*	0.18*	0.16*	0.09 (0.087)	0.14*	0.14*	0.26*	0.25*
Elevated LDL-c	0.14*	0.15*	0.12 (0.021)	0.08 (0.131)	0.09 (0.066)	0.11 (0.032)	0.19*	0.17*
Low HDL-c	0.20*	0.15*	0.14*	0.02 (0.716)	−0.04 (0.398)	0.14*	0.09 (0.070)	0.12 (0.015)
Elevated Triglycerides	0.13*	0.19*	0.12 (0.017)	0.15*	0.17*	0.06*	0.21*	0.15*
Framingham risk score	0.07 (0.162)	0.24*	0.06 (0.237)	0.37*	0.28*	0.01 (0.895)	0.23*	0.11 (0.038)

Notes: *Means p<0.01, r – Pearson's correlation coefficient for comparison of continuous variables or Point-Biserial correlation for comparison between continuous and binary variables.

Abbreviations: SBP, systolic blood pressure; DBP, diastolic blood pressure; BP, blood pressure; HbA1c, glycated hemoglobin; FBG, fasting blood glucose; LDL-c, low density lipoprotein cholesterol; HDL-c, High density lipoprotein cholesterol; BMI, body mass index; MUAC, mid upper arm circumference; WHR, waist hip ratio; NC, neck circumference; HC, hip circumference; WC, waist circumference; WHtR, waist-height ratio.

4. **Serum Uric Acid**: WC (r=0.25), NC (r=0.26), WHR (r=0.25), and weight (r=0.25) had significant but weak positive correlations with serum uric acid.

Framingham Risk Score: NC (r=0.37), waist circumference (r=0.23), and weight (r=0.24) had significant but weak correlations with the Framingham risk score.

Discussion

This study sought to evaluate the correlations between anthropometric measurements with cardiometabolic biomarkers and the 10-year CVD risk score among PWH in Uganda. While anthropometric indices were strongly intercorrelated, their correlation with cardiometabolic biomarkers and the FRS were generally weak.

The high degree of intercorrelation of anthropometric measurements suggests that these indices capture similar aspects of body composition, emphasizing their utility as simple and cost-effective tools for assessing central obesity in resource-limited settings. These findings are consistent with existing literature, which highlights the close relationships among anthropometric measures as markers of overall and central adiposity, particularly a very strong correlation between the WC and WHtR.[27] Strong correlations of MUAC with weight (r = 0.6)[28] and MUAC with BMI (r = 0.85)[29] among PWH have been also observed in other studies in Uganda and Ethiopia, respectively.

The weak correlation between the anthropometric measurements with the cardiometabolic biomarkers implies that they have little utility in identifying which PWH need additional laboratory workup for hyperglycemia and dyslipidemia. Further, the weak correlation with the FRS raises concern about their use in predicting the 10-year CVD risk among PWH. Nonetheless, the WC consistently performed better than other anthropometric measurements, albeit showing a weak correlation with systolic BP, diastolic BP, hypertension, uric acid, FBG, and cholesterol. This is in tandem with the CKD-Africa Cohort study, which found weak correlations between the WC with most cardiometabolic biomarkers, including the diastolic BP and FBG among PWH of African ancestry.[30] Data from the National Health and Nutrition Examination Survey also found that the WC performs better than the BMI in predicting hypertension, dyslipidemia, and the metabolic syndrome.[31] Despite its promising role, several cut-offs of the WC have poor diagnostic accuracy for all cardiometabolic biomarkers.[30] There is a need for specific validated cut-offs for anthropometric measurements for PWH.[11] Contrary to our findings, in a Nigerian study of 998 individuals, WHR was a better predictor of hypertension than WC while the WC best predicted glucose intolerance.[32] This is likely because our population was PWH.

Several mechanisms may explain the observed weak correlations between anthropometric measurements and cardiometabolic profiles in our cohort. HIV-related changes in body composition, such as lipodystrophy and sarcopenia, can alter fat distribution and muscle mass in ways that are not fully captured by standard anthropometric indices.[33] Additionally, metabolic abnormalities in PWH, including dyslipidemia and insulin resistance, may arise from chronic inflammation and antiretroviral therapy—particularly older regimens—independently of body size.[5] In the primary study from which our study population was drawn, cotrimoxazole use, dolutegravir-based ART, and a history of prior opportunistic infections were variably associated—and in some cases interacted—with high BMI, central obesity, diabetes, and dyslipidemia.[20] Notably, these associations were independent of traditional anthropometric measurements.

Finally, we sought to evaluate the correlation between anthropometric measurements and the 10-year CVD risk score among PWH in Uganda. The FRS is a tool widely used among different populations to assess the 10-year risk of developing CVD and shows robust performance among PWH compared to alternative prediction models.[22] In our study, the NC had the best but weak positive correlation with the FRS. Similarly, Koppad et al found the NC to be better correlated (r=0.42) with the FRS compared to the BMI (r = 0.18).[26] Adequate cut-offs for NC to predict CVD risk among PWH are unknown but may be varied between sexes.[12] Generally, the weak correlation between the anthropometric measures with the cardiometabolic biomarkers and the FRS highlights the limitations of anthropometric indices as standalone predictors of cardiometabolic risk in PWH and underscores the need for more comprehensive risk assessment approaches, including laboratory measurements. Contrary to our observations, a recent study in Uganda showed that BMI-based FRS scores correlated well with the laboratory-based FRS scores at predicting the 10-year CVD risk among PWH, although the correlation of either score with pre-existent carotid intima-media thickness was weak (r<0.4).[34] There is, therefore, a need for prospective studies to evaluate the performance of anthropometric vs laboratory-based measurements in predictive CVD in PWH in SSA. Further, there is a need to strengthen access to laboratory-based diagnostics within HIV care programs. These results also support the integration of routine biochemical screening into primary HIV care and the development of HIV-specific CVD risk assessment tools other than anthropometric measurements.

Our study has notable limitations. Its cross-sectional design limits the ability to establish causation or assess longitudinal changes in cardiometabolic profiles, which would be essential for understanding dynamic interactions over time. The findings may also have limited generalizability, as participants were drawn from a single hospital and may not reflect the broader population in other regions or contexts. Furthermore, key confounding factors such as dietary habits, genetic predispositions, and physical activity were not extensively analyzed, potentially influencing the observed correlations.

Conclusions

This study found strong intercorrelations among anthropometric measurements but revealed their limited utility in predicting cardiometabolic biomarkers and 10-year CVD risk among PWH in Uganda. While WC emerged as the strongest anthropometric correlate of cardiometabolic outcomes, its associations with most biomarkers and CVD risk remained weak. These findings underscore the limitations of anthropometric indices as reliable standalone predictors of cardiometabolic risk, especially in resource-limited settings where laboratory assessments may not be routinely available. Despite their practicality for initial screening, anthropometric measures must be supplemented with laboratory-based evaluations to provide a comprehensive assessment of CVD risk in this population bearing in mind the feasibility and cos-effectiveness of the lab-based evaluations in low-income settings.

Data Sharing Statement

The datasets used and/or analysed during the current study are available from the corresponding author on reasonable request.

Ethics Approval and Informed Consent

All study procedures were conducted in accordance with the Declaration of Helsinki. The study was approved by the Mildmay Uganda Research Ethics Committee (MUREC-2023-240), and the Uganda National Council of Science and Technology (HS2991ES) prior to participant recruitment. Study participants provided written informed consent before study procedures were performed.

Author Contributions

All authors made a significant contribution to the work reported, whether that is in the conception, study design, execution, acquisition of data, analysis and interpretation, or in all these areas; took part in drafting, revising or critically reviewing the article; gave final approval of the version to be published; have agreed on the journal to which the article has been submitted; and agree to be accountable for all aspects of the work.

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Disclosure

The authors declare no competing interests in this work.

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