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Multimorbidity of cardiometabolic diseases: a cross-sectional study of patterns, clusters and associated risk factors in sub-Saharan Africa

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ABSTRACT

Objective To determine the patterns of cardiometabolic multimorbidity and associated risk factors in sub-Saharan Africa (SSA).

Design We used data from the WHO STEPwise approach to non-communicable disease risk factor surveillance cross-sectional surveys conducted between 2014 and 2017.

Participants The participants comprised 39, 658 respondents aged 15–69 years randomly selected from nine SSA countries using a multistage stratified sampling design.

Primary outcome measure Using latent class analysis and agglomerative hierarchical clustering algorithms, we analysed the clustering of cardiometabolic diseases (CMDs) including high blood sugar, hypercholesterolaemia, hypertension and cardiovascular diseases (CVDs) such as heart attack, angina and stroke. Clusters of lifestyle risk factors: harmful salt intake, physical inactivity, obesity, tobacco and alcohol use were also computed. Prevalence ratios (PR) from modified Poisson regression were used to assess the association of cardiometabolic multimorbidity with sociodemographic and lifestyle risk factors.

Results Two distinct classes of CMDs were identified: relatively healthy group with minimal CMDs (95.2%) and cardiometabolic multimorbidity class comprising participants with high blood sugar, hypercholesterolaemia, hypertension and CVDs (4.8%). The clusters of lifestyle risk factors included alcohol, tobacco and harmful salt consumption (27.0%), and physical inactivity and obesity (5.8%). The cardiometabolic multimorbidity cluster exhibited unique sociodemographic and lifestyle risk profiles. Being female (PR=1.7, 95% CI (1.5 to 2.0), middle-aged (35–54 years) (3.9 (95% CI 3.2 to 4.8)), compared with age 15–34 years, employed (1.2 (95% CI 1.1 to 1.4)), having tertiary education (2.5 (95% CI 2.0 to 3.3)), vs no formal education and clustering of physical inactivity and obesity (2.4 (95% CI 2.0 to 2.8)) were associated with a higher likelihood of cardiometabolic multimorbidity.

Conclusion Our findings show that cardiometabolic multimorbidity and lifestyle risk factors cluster in distinct patterns with a disproportionate burden among women, middle-aged, persons in high socioeconomic positions, and those with sedentary lifestyles and obesity. These results provide insights for health systems response in

STRENGTHS AND LIMITATIONS OF THIS STUDY

⇒ Data used in this analysis are from nationally representative population-based surveys conducted in nine countries in sub-Saharan Africa using a standardised WHO-STEPwise approach to non-communicable disease risk factor surveillance protocol. Hence, the findings are generalisable to the populations of these countries.

⇒ The screening for cardiometabolic diseases is based on direct measures of blood pressure, anthropometry, key biomarkers and self-reports thereby allowing for an objective assessment of multimorbidity.

⇒ This study provides crucial evidence on population-based cardiometabolic multimorbidity patterns among broader age ranges comprising young, middle-aged older persons.

⇒ Data used in the analysis are from cross-sectional studies; thus, it is not possible to draw causal inferences for cardiometabolic multimorbidity and temporal associations with sociodemographic and lifestyle risk factors. However, the findings provide useful insights for policy makers and health service providers to prioritise risk-centred approaches for prevention, early detection and treatment of cardiometabolic multimorbidity.

SSA to focus on these clusters as potential targets for integrated care.

INTRODUCTION

Cardiometabolic diseases (CMDs) are the leading cause of global mortality and disability.[1] Over half of the global burden of non-communicable diseases (NCDs) are attributable to CMDs that share four major risk factors: harmful alcohol use, unhealthy diet, tobacco use and physical inactivity.[2 3] Three-quarters of the global CMD-related mortality occurs in low-income and middle-income countries with 30% classified as premature deaths.[4] People living with CMDs often present with multiple conditions including

diabetes mellitus, hypercholesterolaemia, hypertension and stroke.[5–7] Hence the concept of cardiometabolic multimorbidity.

Although CMDs are estimated to take away up to 12 years in life expectancy,[8 9] their onset can be prevented or postponed by the elimination of lifestyle risk factors.[10 11] Most studies have consistently identified cardiometabolic multimorbidity as a common cluster.[12–15] However, there are still several knowledge gaps on the multimorbidity spectrum in sub-Saharan Africa (SSA). First, literature is scarce on clustering CMDs and behavioural risk factors because extant evidence has not applied statistical methods to separate the random and non-random co-occurrence.[16–19] Moreover, most studies have mainly focused on analysing the most prevalent CMD combinations.[16–20] The prevalence of different disease combinations is significantly associated with the prevalence of the individual comorbid diseases in question. Hence, a high prevalence of a particular multimorbidity combination does not provide sufficient evidence to support a non-random co-occurrence.[21] Accounting for the random coexistence of multimorbidity requires rigorous assessment of multimorbidity clusters and lifestyle risk factors.[22]

Evidence of clustering of CMDs and lifestyle risk factors is needed to prioritise healthcare services for the most frequently co-occurring combinations.[23] However, the methodological differences in the conceptualisation of multimorbidity in previous studies have hindered the comparison of findings.[13 24] Furthermore, most studies have been conducted among older age groups in primary care settings where multimorbidity are more likely to occur.[13 24] To date, little research in SSA has investigated multimorbidity patterns among broader age ranges from the general population.

This study, therefore, sought to investigate patterns and clusters of cardiometabolic multimorbidity and associated factors among persons aged 15–69 years using nationally representative WHO STEPwise surveys from nine countries in SSA.

METHODS

Study design

We used data from the WHO STEPwise approach to NCD risk factor surveillance (STEPS) surveys in SSA. Details of the data collection methods have been published elsewhere.[25] Briefly, STEPS surveys are nationally representative population-based cross-sectional surveys of risk factors for NCDs in participants aged 15–69 years. The WHO STEPS surveys aims to provide baseline national estimates for NCD indicators to inform health policies in the study countries.[26]

A standard sampling protocol for the WHO STEPS survey was used in all the study countries.[27] The participants were selected using a multistage stratified sampling design. First, sampling clusters or enumeration areas (EAs) were selected using probability proportional to the size of the number of households in the cluster. Second, samples of households were randomly drawn from a household listing in the cluster. Eligible participants comprised all listed household members aged 18–69 years residing in the sampled households for at least 6 months preceding the survey. In some countries, the minimum age was 15 years.[28–30] Finally, the Kish sampling grid was used to randomly select one study participant from a list of all eligible household members.[25]

Data abstraction

Data used in the current study were collected using interviewer-administered structured questionnaires modified from the WHO STEPS tool.[25] The data were from self-reports and direct measurements of anthropometry and key biomarkers. The variables were measured using the WHO criteria.[27] Self-reported information comprised sociodemographic characteristics such as age, sex, education and employment; behavioural risk factors such as physical inactivity, tobacco and alcohol use, harmful salt consumption; and clinical histories of high blood sugar, hypercholesterolaemia, hypertension and cardiovascular diseases (CVDs) (heart attack, angina and stroke). The physical measurements comprised screening for blood pressure and anthropometrics such as weight (kg) and height (m). The biochemical measurements comprised fasting blood samples for cholesterol and blood sugar measurements in mmol/L or mg/dL. Random blood glucose was collected for 117/39 658 participants who failed to fast as instructed. The measurements of the variables used in this study are shown in table 1.

Data inclusion and exclusion criteria

We used a two-stage inclusion criteria for the present study (see online supplemental file 1). The first step involved the selection of eligible study countries while in the second step, eligible participants were selected from the latest round of the STEPS survey in each of the study countries (see online supplemental file 2). In the first step, a country was eligible for inclusion in the analysis if it met the following criteria: (1) Had data collected between 2000 and 2020; (2) The survey was nationally representative and (3) Had data on key variables comprising blood sugar, cholesterol, body mass index, blood pressure and CVD status. Others comprised age, sex, education, employment, alcohol consumption, smoking, diet and physical activity. In the second step, eligible participants were included in the analysis if they were not pregnant. In the end, data from 9 countries with 39 658 participants were included in the analysis (see online supplemental file 3).

Definition of variables

The outcome variable for the present analysis was defined as the clustering of CMDs comprising high blood sugar, hypercholesterolaemia, hypertension and CVDs (heart attack, angina and stroke). The explanatory variables included sociodemographic characteristics: age, sex, education level and employment status. Other

Table 1 Measurements of study of the variables

Variable	Measurement
Sociodemographic factors	
Age	Young age (15–34 years), middle-age (35–54 years), older age (55–69 years)
Sex	Male, female
Education	No formal education, primary, secondary or tertiary
Employment	Unemployed, employed
Self-reported lifestyle risk factors	
Physical activity	≥150 min/week of MPA or ≥75 min/week of VPA or ≥150 min/week of MVPA
Harmful salt intake	Always or often adding salt to cooked food
Alcohol use	Current alcohol use
Current tobacco use	Current smoking and/or tobacco use
BMI	
Obesity	BMI ≥30 kg/m^2 for adult participants (18+years) or BMI-for-age-sex ≥95th percentile in participants aged <18 years
Cardiometabolic diseases	
High blood sugar	FBS concentration of ≥7 mmol/L (126 mg/dL) or RBS concentration of ≥11.1 mmol/L (200 mg/dL) and/or a previous diagnosis of diabetes mellitus by a professional healthcare provider and/or being on treatment for diabetes.
Cardiovascular Disease	Having a previous diagnosis of heart attack or angina or a stroke
Hypertension	SBP ≥140 or DBP ≥90 mm Hg and/or a previous diagnosis of hypertension by a professional healthcare provider and/or being on antihypertensive therapy.
Hypercholesterolaemia	Total cholesterol levels ≥5.2 mmol/L (202.8 mg/dL) or having a previous diagnosis of high cholesterol by a professional healthcare provider and/or being on treatment for elevated cholesterol

BMI, body mass index; DBP, diastolic blood pressure; FBS, fasting blood sugar; MPA, moderate-to-vigorous physical activity; MVPA, moderate-to-vigorous physical activity; RBS, random blood sugar; SBP, systolic blood pressure; VPA, vigorous physical activity.

covariates comprised clusters of multiple lifestyle risk factors including harmful salt intake, physical inactivity, obesity, tobacco use and alcohol consumption. Clusters were named based on their unique dominant CMDs and risk profiles.

Data analysis

Applying sample weights

We accounted for the complex survey design using the svyset command in Stata, by defining clusters and sampling weights. The original country-level datasets were weighted using the probability of selection at each stage of sampling. Thus, the participants' weight was equal to the inverse of the product of the probability of the selection of the EA or sampling cluster, the probability of household selection, the probability of selection within the household and the age–sex distribution of the study country.

Characteristics of participants were summarised using frequencies and percentages. Given the exclusion of participants with missing data on the key variables, we compared the characteristics of the participants with complete data and those with incomplete data and found no differences between the two groups based on age, sex and employment status (See online supplemental file 4).

Latent class analysis

We used latent class analysis (LCA) to identify distinct groups of cardiometabolic multimorbidity and lifestyle risk factors. The LCA is a structural equation modelling-based approach used to identify groups of participants with homogeneous response patterns to a set of observed variables.[31] We determined the optimal number of latent classes using the adjusted Bayesian information criterion (BIC). The BIC has been previously used as a robust indicator for determining the optimal number of classes for latent variables.[32 33] First, the BIC was used to compare several plausible models. The model with the lowest values of BIC was finally selected as the best-fitting model.[34 35] The posterior probabilities were used to determine the likelihood of class membership. Finally, the participants were grouped into the classes with the highest-class probability.

Hierarchical cluster analysis

We conducted a supplementary analysis of the cardiometabolic multimorbidity patterns and clustering of lifestyle risk factors using the agglomerative hierarchical cluster analysis.[36] First, the proximity index grouped individual CMDs and lifestyle risk factors into a single cluster. Second, the individual clusters were gradually merged

Table 2 Sociodemographic and health characteristics of the study participants

	Benin	Botswana	Ethiopia	Kenya	Malawi	Sudan	Swaziland	Uganda	Zambia	Pooled data
	n=4645	n=3302	n=8184	n=3986	n=3640	n=6559	n=2461	n=3413	n=3468	n=39658
Age										
15–34	56.5	62.3	64.5	57.6	54.3	55.9	64.7	56.3	59.2	59.2
35–54	33.9	28.0	27.3	32.3	35.0	33.7	24.9	32.6	32.2	31.2
55–69	9.6	9.7	8.2	10.1	10.6	10.3	10.4	11.1	8.6	9.6
Sex										
Male	52.1	51.4	56.0	50.5	48.9	55.9	48.2	49.6	50.8	53.1
Female	47.9	48.6	44.0	49.5	51.1	44.1	51.8	50.4	49.2	46.9
Education										
No formal education	46.7	7.0	41.3	11.7	10.6	40.1	5.9	15.1	7.1	27.6
Primary	30.9	20.9	47.2	45.9	66.7	27.9	46.6	42.1	44.6	43.3
Secondary	15.9	53.4	7.1	31.5	20.1	21.0	38.6	34.4	40.4	21.5
Tertiary	6.5	18.7	4.4	10.9	2.6	11.1	9.0	8.5	7.9	7.6
Employment										
Unemployed	26.6	72.5	92.6	40.0	61.6	51.3	63.9	37.0	49.3	61.0
Employed	73.4	27.5	7.4	60.0	38.4	48.7	36.1	63.0	50.7	39.0
Lifestyle risk factors										
Tobaco use	9.9	20.7	4.9	13.2	12.4	15.8	8.3	11.7	15.8	11.0
Alcohol use	37.2	34.0	43.3	24.6	21.6	2.5	18.1	36.1	27.3	27.9
Harmful salt intake	11.4	98.6	60.2	23.2	17.6	32.1	17.9	21.6	38.7	37.5
Physical inactivity	17.7	25.6	7.1	7.9	4.3	17.5	17.5	5.6	14.5	9.8
Obesity	8.6	11.7	1.1	9.1	5.1	10.1	19.5	4.6	7.2	5.8
Cardiometabolic diseases										
Hypercholesterolaemia	13.9	8.8	3.3	6.5	5.6	11.1	8.5	4.8	4.7	6.2
High blood sugar	6.5	3.9	2.2	2.5	1.8	7.4	5.5	1.8	7.4	3.7
Hypertension	31.0	36.2	18.1	27.2	20.3	33.0	30.9	27.4	24.5	24.9
CVD	4.8	7.3	3.4	5.7	7.8	3.4	4.7	9.2	3.6	4.9

Data presented as weighted row %, unless otherwise specified, CVDs include heart attack, angina and stroke.
CVD, cardiovascular diseases.

with the most closely related clusters until a single cluster with all the elements was obtained. We used the average linkage method to accommodate the spread of the clusters.[36] The number of clusters was assessed using a dendrogram and Jaccard similarity coefficient. In summary, the Jaccard coefficient is a measure of similarity between two sets or clusters expressed as a percentage. The higher the percentage, the more similar the two clusters are.[37]

Modified Poison regression

We used modified Poisson regression to assess the sociodemographic variables and clusters of lifestyle risk factors associated with cardiometabolic multimorbidity. The sociodemographic variables comprising age, sex, education level, employment status and clusters of lifestyle risk factors were regressed against a dummy outcome variable indicating whether the participant was in class 1 (healthy class with minimal CMDs) or class 2 (cardiometabolic multimorbidity). The selection of the sociodemographic and lifestyle risk factors for the multivariable model was based on the variables conceptualised from the WHO's theoretical framework on the social determinants of NCDs[38] as more traditional level p values such as 0.05 used to select variables can fail in identifying variables known to be important.[39] We adjusted for country of residence by including the country dummy variable in the models, as in previous publications from WHO surveys.[40–42] We found no multicollinearity among the independent variables based on the assessment of variance inflation factors.[43] The adjusted prevalence ratios (PRs) and 95% CI from modified Poisson regression were used to determine the sociodemographic and lifestyle risk factors associated with cardiometabolic multimorbidity.

All statistical analyses were carried out in Stata V.15 (StataCorp).

Patient and public involvement

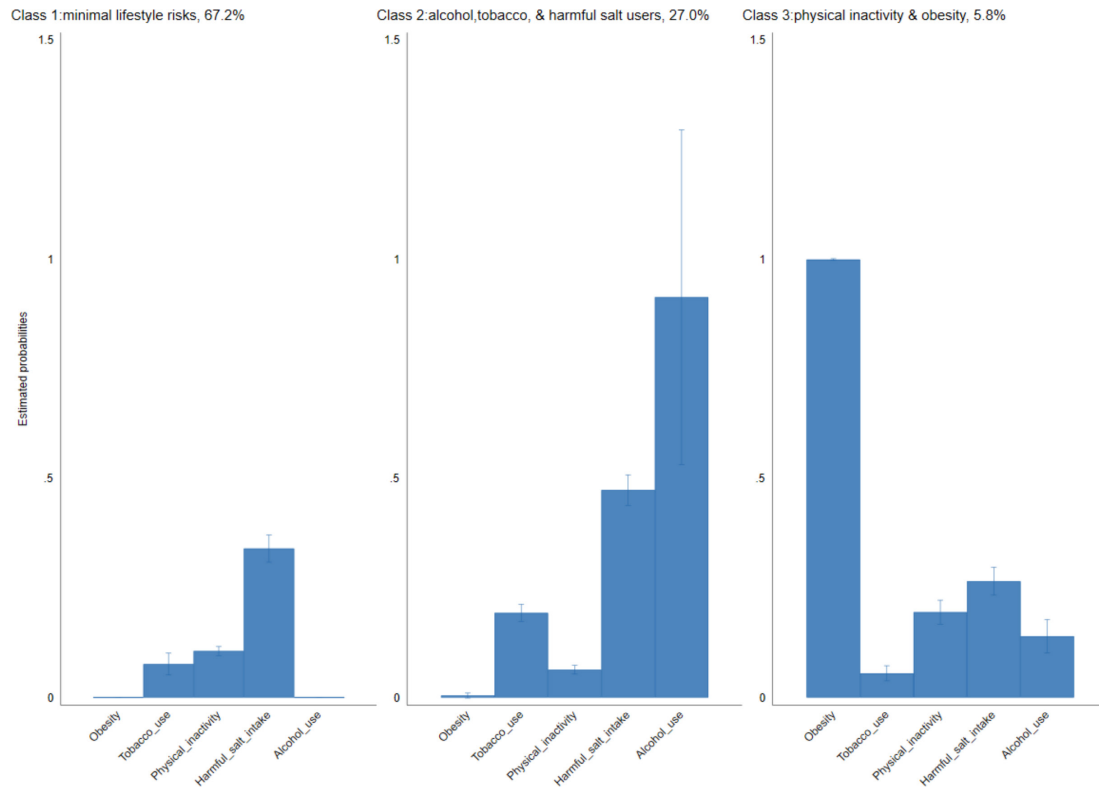Patients and/or the public were not involved in the design, conduct, reporting or dissemination of this research.

Figure 1 Latent classes of lifestyle risk factors.

RESULTS
Characteristics of participants
In total, 39 658 participants were included in the analysis. Table 2 shows the characteristics of the study participants. In general, most of the participants were women, belonged to the youngest age group (15–34 years), had a primary level of education and were unemployed.
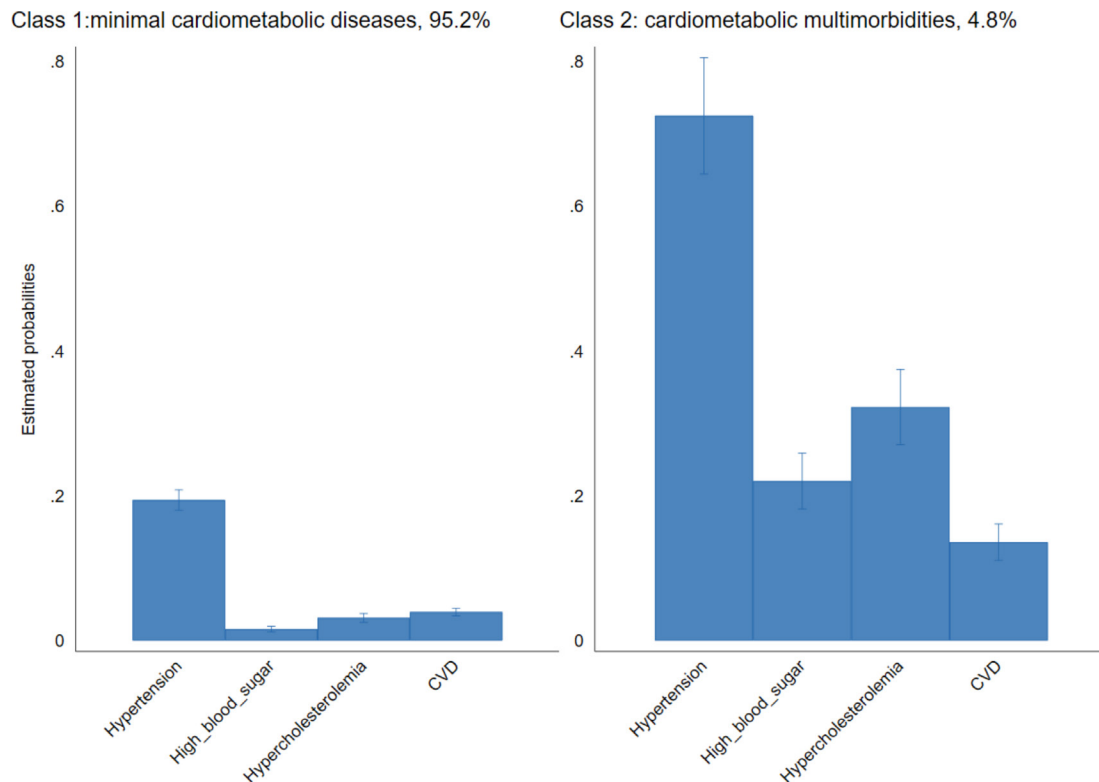

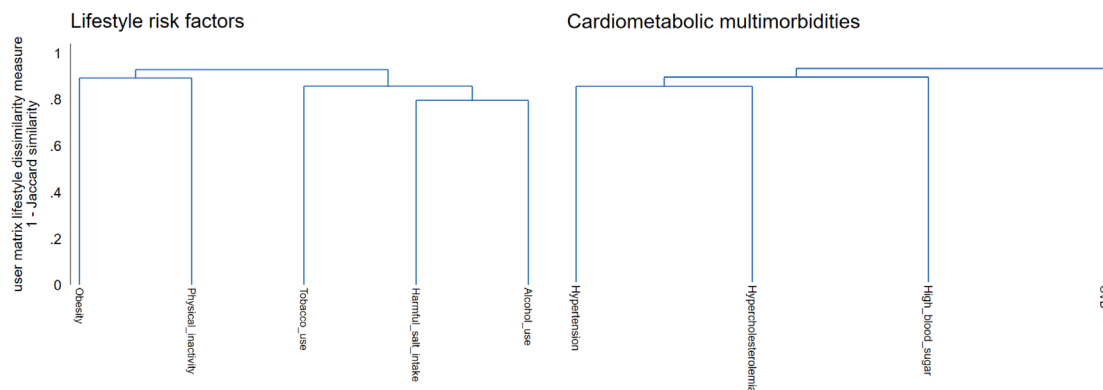**Figure 2** Latent classes of cardiometabolic diseases.

Figure 3 Dendrogram of lifestyle risk factors and cardiometabolic diseases.

Harmful salt intake (37.5%) and alcohol use (27.9%) were the most prevalent lifestyle risk factors. The most prevalent CMD was hypertension (24.9%). Varying patterns in the distribution CMDs and lifestyle risk factors were observed among the study countries. Tobacco use (20.7%), harmful salt intake (98.6%), physical inactivity (25.6%) and hypertension (36.2%) were highest in Botswana. Ethiopia had the highest prevalence of alcohol use (43.3%). Obesity and hypercholesterolaemia were highest in Swaziland (19.5%) and Benin (13.9%). Sudan and Zambia had the highest prevalence of high blood sugar (7.4%) while CVD prevalence was highest in Uganda (9.2%).

Findings of LCA
Clustering of lifestyle risk factors
The classes of lifestyle risk factors are shown in figure 1. We compared LCA models with 1–4 classes (see online supplemental file 5). The three-class model had the lowest BIC and thus was selected as the best-fit model. Class one comprised participants with minimal lifestyle risks (67.2%). Class two included participants with high probabilities of alcohol use, smoking and harmful salt consumption (27.0%). Class three comprised participants with the highest probability of physical inactivity and obesity (5.8%).

Cardiometabolic multimorbidity classes
The classes of CMDs are shown in figure 2. We ran LCA models from 1 to 4 classes selecting the two-class model based on indices of fit (see online supplemental file 5). The two-class model had the lowest BIC and thus was selected as the best-fit model. Class one (interpreted as the 'relatively healthy group') comprised participants with minimal multimorbidity (95.2%). Class two (cardiometabolic multimorbidity) included participants with the highest probability of high blood sugar, hypercholesterolaemia, hypertension and CVDs (4.8%).

Hierarchical cluster analysis findings
As a supplementary analysis, we also calculated cardiometabolic multimorbidity patterns and clustering of lifestyle risk factors using the agglomerative hierarchical cluster analysis. Figure 3 shows the hierarchical tree plot (dendrogram). The dendrogram displays the agglomeration schedules at which CMDs and lifestyle risk factors are combined. In general, the findings were similar to those obtained using LCA. The hierarchical clustering algorithms revealed two distinct groupings of lifestyle risk factors. Based on the proximity coefficients, physical inactivity and obesity formed the first cluster. Alcohol use, harmful salt intake and tobacco use combined to form the second cluster. The proximity coefficients from the hierarchical cluster analysis revealed clustering of hypertension, hypercholesterolaemia, high blood sugar and CVDs.

Distribution of cardiometabolic multimorbidity by sociodemographic and lifestyle risk factors
The distribution of cardiometabolic multimorbidity by sociodemographic and lifestyle risk factors is presented in table 3. The clustering of cardiometabolic multimorbidity (hypertension, high blood sugar, hypercholesterolaemia and CVD) was highest in middle-aged and older participants, females, employed and those with tertiary education. Varying patterns in the distribution of cardiometabolic multimorbidity were observed among the study countries. The prevalence of cardiometabolic multimorbidity was highest in Sudan and Botswana (9.9% and 9.3%) and lowest in Ethiopia (2.0%).

Sociodemographic and lifestyle risk factors associated with cardiometabolic multimorbidity
Figure 4 shows the sociodemographic and lifestyle risk factors associated with cardiometabolic multimorbidity. Being female (PR=1.7, 95% CI (1.5 to 2.0), middle-aged (35–54 years) (3.9 (95% CI 3.2 to 4.8)) and older age (55–69 years) (3.9 (95% CI 3.2 to 4.8)), compared with age 15–34 years were associated with a higher likelihood of cardiometabolic multimorbidity. Participants in the highest socioeconomic position such as tertiary education (2.5 (95% CI 2.0 to 3.3)) vs no formal schooling and those employed (1.2 (95% CI 1.1 to 1.4)) vs unemployed were more likely to have cardiometabolic multimorbidity. The likelihood of cardiometabolic multimorbidity was higher among participants with co-occurring physical inactivity

Table 3 Distribution of cardiometabolic multimorbidity by sociodemographic and lifestyle risk factors

Weighted row%	Latent classes	
	Class1: relatively healthy	Class 2: cardiometabolic multimorbidity
	Minimal cardiometabolic diseases	Hypertension, high blood sugar, hypercholesterolaemia and CVD
N	36 618	3040
Age*		
18–34	98.3	1.7
35–54	92.3	7.7
55–69	85.9	14.1
Sex*		
Male	96.3	3.7
Female	93.9	6.1
Employment*		
Unemployed	96.2	3.8
Employed	93.7	6.3
Education*		
No schooling	95.0	5.0
Primary	96.6	3.4
Secondary	94.4	5.6
Tertiary	90.4	9.6
Country*		
Benin	90.7	9.3
Botswana	92.8	7.2
Ethiopia	98.0	2.0
Kenya	95.3	4.7
Malawi	96.7	3.3
Sudan	90.2	9.9
Swaziland	92.4	7.7
Uganda	96.5	3.5
Zambia	94.5	5.5
Latent classes of lifestyle risk factors*		
Class 1: minimal lifestyle risks	95.8	4.2
Class 2: alcohol, tobacco and harmful salt users	97.0	3.0
Class 3:physical inactivity and obesity	79.9	20.1
Total	95.2	4.8

Data presented as weighted row %, unless otherwise specified.
*p<0.05.
CVD, cardiovascular disease.

and obesity (2.4 (95% CI 2.0 to 2.8)) compared with those with minimal lifestyle risk factors.

DISCUSSION

In this study, we examined the patterns of cardiometabolic multimorbidity and associated risk factors in persons aged 15 years and older in SSA. Two distinct classes of CMDs were identified: a relatively healthy group with minimal CMDs and a cardiometabolic multimorbidity class comprising participants with high blood sugar, hypercholesterolaemia, hypertension and CVDs. Three clusters of lifestyle risk factors were yielded. Class 1 comprised participants with minimal lifestyle risks. Class 2 included alcohol users, smokers and harmful salt consumers. Class 3 comprised clustering of physical inactivity and obesity. Our findings show that cardiometabolic multimorbidity cluster in distinct patterns with a disproportionate burden among women, middle-aged, persons in the highest socioeconomic positions, and those with sedentary lifestyles and obesity.

The clusters of cardiometabolic multimorbidity identified in our study have similarities with findings from other studies in SSA.[44 45] Several underlying pathophysiological mechanisms could explain the clustering of high blood sugar, hypercholesterolaemia, hypertension and CVDs. Insulin resistance is known as a possible mechanism explaining the clustering of CMDs.[46–48] The abnormalities in the metabolism process could be due to in part insulin resistance which may also lead to defects in vascular reactivity.[49] The clustering of lifestyle risk factors such as smoking, alcohol use and harmful salt consumption in our study could be due to the interplay among various sociobehavioural factors that affect smoking, drinking behaviour and diet.[50] This was consistent with findings from other studies in different parts of the world.[50–52] Given that CMDs share common lifestyle risk factors,[2 3] our results provide crucial insights into the need to scale up population-level primary and secondary prevention programmes. Primary prevention should target co-occurring lifestyle risk factors. Previous studies have shown that healthy lifestyles in early life often persist into adulthood and old age, preventing or delaying CMDs.[53] Secondary prevention should target persons living with CMDs, such as regular screening for multimorbidity, self-monitoring and adopting healthy lifestyles to prevent or delay the onset of multimorbidity.

The gender disparity in the distribution of cardiometabolic multimorbidity observed in our study may be partly attributed to the inequalities in occupational and domestic activities and the gender differences in risk factors for CVDs such as lifestyle and diet.[54 55] Our results suggest that cardiometabolic multimorbidity is not limited to older persons but is a common phenomenon among middle-aged persons in the study countries. These results mirror those of several multimorbidity studies in support of the emerging evidence on the high burden of multimorbidity in middle-aged persons.[53 56–58] Studies conducted in Brazil, Guatemala, India, the Philippines and South Africa have also shown that people living in low-income and middle-income countries tend to experience CMDs much earlier in life than their counterparts living in high-income countries due to socioeconomic hardships and poor access to healthcare services.[59–61]

Similar to previous studies,[62–64] our results show that increasing levels of educational achievements and being
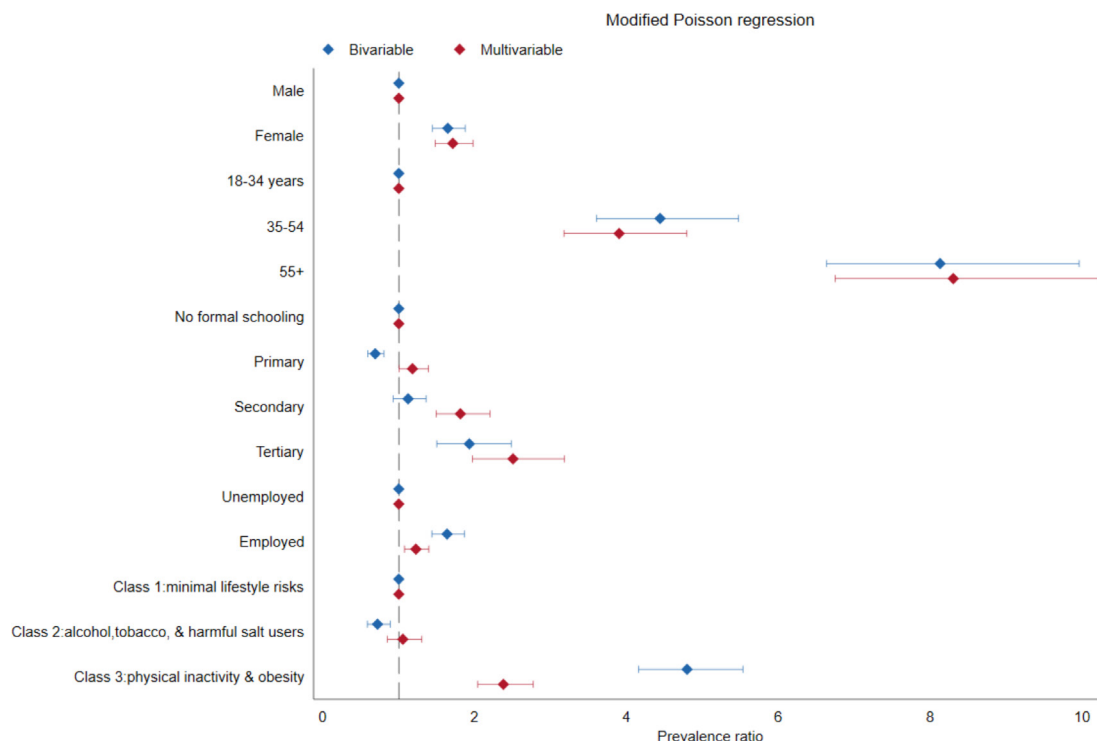
Figure 4 Sociodemographic and lifestyle risk factors associated and cardiometabolic multimorbidity. Adjusted for study countries; cardiometabolic multimorbidity was defined as the clustering of hypercholesterolemia, hypertension, high blood sugar and CVDs.

employed were associated with a greater likelihood of cardiometabolic multimorbidity. This may be due to the fact that with higher education and employment also comes affluence,[62–64] and greater access to alcohol, tobacco and unhealthy diets.[65] However, other studies have also shown that higher education achievement was also associated with a low likelihood of clustering of multiple behavioural risk factors for CVDs, possibly because a higher level of education may also increase both awareness of, and capacity for lifestyle modification.[50 66] Further studies on the socioeconomic determinants of cardiometabolic multimorbidity are needed to elucidate these results.

The likelihood of cardiometabolic multimorbidity was higher among participants with co-occurring physical inactivity and obesity compared with those with minimal lifestyle risk factors. This finding is in line with previous studies that pointed in the same direction.[67–69] The mechanisms through which physical activity increases the risk of cardiometabolic multimorbidity are known. Previous physical activity intervention studies have demonstrated consistent improvements in various CVD risk factors such as hypertension,[70] HDL cholesterol,[71] C reactive protein and other inflammatory markers.[72 73] Consequently, further longitudinal studies are needed to elucidate the most critical sociodemographic factors attributable to the clustering of physical inactivity and obesity and its long-term effects on cardiometabolic multimorbidity.

Overall, our findings have two main implications. First, there is a need for further policy discourse on the integrated management of CMDs in primary care settings in

SSA. The clustering of CMDs and lifestyle risk factors in the population is important for clinicians, policy makers and researchers in prioritising the needs and care processes for patients living with or at risk of multimorbidity. A paradigm shift towards comprehensive care may enable patients presenting with CMDs at primary care to be regularly screened for other chronic conditions. A shift away from fragmented care may also improve access to quality healthcare services, especially in SSA where persons living with CMDs remain undiagnosed for several years and the majority of those on treatment often remain uncontrolled.[74] Second, our study provides baseline estimates for future researchers to design longitudinal studies on the burden and aetiology of the most common clusters of CMDs in SSA.

Strengths and limitations

Data used in this analysis are from nationally representative population-based surveys conducted in nine countries in SSA using a standardised WHO-STEPS protocol. Hence, the findings are generalisable to the populations of these countries. Second, most previous studies were conducted among older age groups in primary care settings where multimorbidities are more likely to occur.[13 24] Our study bridges this gap by providing crucial evidence on population-based multimorbidity patterns among broader age ranges comprising young, middle-aged and older persons. Third, the data used are based on direct measures of blood pressure, anthropometry, key biomarkers and self-reports allowing for a more

objective screening for CMDs than self-reporting used in over three-quarters of previous studies.[75]

Limitations stem from the fact that the data used in the analysis are from cross-sectional studies thus; it, is not possible to draw causal inferences for cardiometabolic multimorbidity and temporal associations with sociodemographic and multiple lifestyle risks. Moreover, our study does not give an idea of the index disease in the multimorbidity clusters identified. Second, the screening for CVDs such as heart attack, angina and stroke was based on self-reported history of clinical diagnosis, which may have led to information bias, possibly underestimating the prevalence of CVDs. Lastly, the current study is based on pooled data sets from several countries; hence, the findings may be limited by the variations in the sociocultural and economic contexts within the study countries.

CONCLUSIONS

Our findings show that cardiometabolic multimorbidity and lifestyle risk factors cluster in distinct patterns with a disproportionate burden among persons in the highest socioeconomic positions, women, the middle-aged and those with sedentary lifestyles and obesity. These results provide useful insights for health systems response in SSA to focus on these clusters as potential targets in the development and segmentation of integrated care for care cardiometabolic multimorbidity. We draw attention to the need for healthcare systems in SSA to prioritise risk-centred management of CMDs by incorporating aggressive approaches for prevention, early detection, treatment and promotion of healthy lifestyles to avert the occurrence of multimorbidity.

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Ethics approval Data used in this study are publicly available on the NCD microdata repository of the WHO (https://extranet.who.int/ncdsmicrodata/index.php/catalog/STEPS)[76] . We obtained formal written permission from the WHO for the surveys included. Since we used publicly available data, no additional approval was required from an institutional ethics review board.

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