

Wealth and Sedentary Time Are Associated With Dietary Patterns Among Preadolescents in Nairobi City, Kenya

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ABSTRACT

Objective: The study aimed to compare dietary patterns in preadolescents in urban areas with different physical activity and socioeconomic profiles in Nairobi, Kenya.

Design: Cross-sectional.

Participants: Preadolescents aged 9–14 years (n = 149) living in low- or middle-income areas in Nairobi.

Variables Measured: Sociodemographic characteristics were collected using a validated questionnaire. Weight and height were measured. Diet was assessed using a food frequency questionnaire and physical activity by accelerometer.

Analysis: Dietary patterns (DP) were formed through principal component analysis. Associations of age, sex, parental education, wealth, body mass index, physical activity, and sedentary time with DPs were analyzed with linear regression.

Results: Three DPs explained 36% of the total variance in food consumption: (1) snacks, fast food, and meat; (2) dairy products and plant protein; and (3) vegetables and refined grains. Higher wealth was associated with higher scores of the first DP ($P < 0.05$).

Conclusions and Implications: Consumption of foods often deemed unhealthy (eg, snacks and fast food) was more frequent among preadolescents whose families were wealthier. Interventions that seek ways to promote healthy lifestyles among families residing in urban areas of Kenya are warranted.

Key Words: dietary patterns, body mass index, physical activity, sedentary time, preadolescents (*J Nutr Educ Behav.* 2023;000:1–9.)

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INTRODUCTION

The increase in obesity in lower-middle-income countries (LMICs) is largely thought to be affected by life-style transition: the change from

traditional diets toward an unhealthy Western dietary pattern that follows economic development and a reduction of occupational, domestic and transportation activity as a result of increased mechanization.¹ Lifestyle

transition affects different population groups depending on the country's economic status.² When a country's economic status (in terms of Gross National Product) improves, and with increasing urbanization, the unhealthy lifestyle leading to obesity shifts from high to low socioeconomic status (SES).

In Kenya, the prevalence of overweight (body mass index [BMI], 25–29.9) and obesity (BMI, > 30) in adult women was 18% and 8%, respectively, in 2008.³ However, the prevalence of women with obesity has been observed to be much higher in urban settings⁴ reaching up to 24%.⁵ Children living in Nairobi were reported to have a prevalence of overweight or obese of 21%, with the majority of the children classified as overweight/obese being female.⁶ Dietary habits of people in Kenya are

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changing from traditional staple foods toward refined grains, especially in urban environments⁷ and in women.^{8,9} However, unhealthy dietary habits are still more common among women with high SES. In cross-sectional studies conducted in Nairobi, the diets of children aged 8–11 years have been generally healthy,⁶ but the reported consumption of fast foods and sweetened beverages have been higher than recommended.¹⁰ Signs of lifestyle transition can also be seen in physical activity. A comparison of physical activity in rural and urban children showed that rural children were more active and engaged significantly less in playing screen games.¹¹ The studies above suggest that Kenya has not reached a developmental position in which the lifestyle transition would have reached the low-SES groups. However, the data were mostly collected earlier than 2010; thus, there is a need for more recent evidence on the situation.

We hypothesize that if the lifestyle transition has moved forward in urban Kenya (ie, Nairobi) during the last 10 years, we would see much smaller (if any) differences between households with higher and lower SES or even an unhealthier lifestyle in the lower SES population in a cross-sectional design. Thus, in this study, we first analyzed dietary patterns (DPs) among preadolescents aged 9–14 years residing in urban areas with different SES profiles in Nairobi. Second, we investigated the association of sociodemographic characteristics and physical activity with these patterns. The design is cross-sectional, with a single time-point assessment. The results are used to compare to earlier studies and make indirect hypotheses about the lifestyle transition.

METHODS

The Kenya-Finland Education and Research Alliance aims to improve education and teaching capacity on noncommunicable diseases (NCDs)-related health behaviors at Kenyatta University, Nairobi. The research part of this project consisted of an in-depth study that aimed at collecting novel and important new data on

NCD-related lifestyles and risk factors in Kenya.

Ethical clearance was sought and received after a full board review from Kenyatta University's Ethical Review Committee (Ethical clearance no. PKU/946/I1002), and a research permit was received from the National Commission for Science, Technology and Innovation. Eligible preadolescents and their guardians were given an informed consent form to sign to show a willingness to participate in the study. The purpose of the study, the interviews to be done, the voluntary nature of participation, and the right to refuse to participate in any part of the study were also explained orally. All questionnaires were available in both English and Swahili.

The cross-sectional data was collected in 2019 from 2 subcounties in Nairobi: Embakasi Central, which represents a low-SES area and is partly an informal settlement, and Langata, which represents a middle-SES area. These 2 areas were chosen to give a wide variation of SES, with mainly the very wealthy population not included. The inclusion criteria were a household with a 9–14-year-old preadolescent who had lived in either area for at least 6 months before the study and whose caregivers provided consent to participate. The exclusion criteria were the documentation of chronic disease conditions impacting diet or any significant illnesses preventing participation (eg, tuberculosis).

One of the main outcomes of the study was preadolescents with overweight/obesity, which was used as the basis for power calculation. According to Broyles et al,¹² expected difference in child BMI z-score between low- and middle-SES in low-income countries is 0.5. When we use 1.0 as the SD, α of 0.05, and power of 80%, the total 2-group sample size is $n = 126$ ($n = 63$ per group). To allow for nonresponse, we aimed to invite 160 households. The final study population comprised 149 households (93% of those invited).

A multistage sampling technique was conducted to identify the households in which data would be collected. In the first stage, Embakasi was purposively selected to represent

low SES (partly an informal settlement), and Langata was selected to represent the middle SES. Next, 5 villages were selected randomly from Kayole North Central Ward (from Embakasi) and 12 estates from Nairobi West Ward (from Langata). The final stage of sampling involved the enumeration of households with a child aged 9–14 years from the selected villages and estates with the assistance of Community Health Volunteers (CHVs). In total, 223 households were enumerated in Embakasi and 173 in Langata. A simple random sampling technique was used to select 80 households from both subcounties. The final number of participating households was 72 for Embakasi and 77 for Langata.

The data were collected using a digital mobile data collection platform (version 2021.2.4, ODK Collect, Open Data Kit).¹³ To determine the sociodemographic characteristics of the participating households, we used parts of a researcher-administered structured questionnaire previously used and validated in the Kenya Demographic and Health Survey.¹⁴ On the questionnaire, multiple sociodemographic characteristics were asked, but the questions used in this study are self-reported sex (male or female; for both adolescents and guardians), date of birth (used for calculating age in years), and education. The question regarding the guardian's education included originally 9 answer categories which were condensed into 6 categories as follows (original categories given in parenthesis): (1) none, (2) not completed primary (adult education, not completed primary), (3) completed primary, (4) not completed secondary, (5) completed secondary, and (6) tertiary education (certificate training, diploma, degree).

Furthermore, the questionnaire included questions on living conditions and the materials from which the household is constructed, such as drinking water sources, latrine facilities, house materials (eg, floor and wall materials), and ownership of assets in the house and other goods (eg, television, radio, bicycle, and car). These items were used to form a wealth index that is a composite measure of a household's cumulative

living standard. It has been widely used in large household surveys conducted by the Demographic and Health Surveys¹⁴ and World Food Programme Surveys.¹⁵ The calculation of the index is explained in the section on statistical analyses.

Preadolescents' height was measured with a portable stadiometer with 0.1 cm accuracy and weight with a portable electric scale to 0.1 kg accuracy in a standardized way. Age- and sex-adjusted z-scores for BMI were calculated using World Health Organization's 2007 growth reference data and World Health Organization's macro package for R-software.¹⁶

The dietary intake data were collected using a 7-day food frequency questionnaire (FFQ), modified from a previously validated FFQ for adults in Nairobi.¹⁷ The FFQ consisted of cultural and urban-specific foods and foods commonly consumed on the basis of a market survey and pretest of the FFQ in the study area. We added locally available foods that are more commonly used among preadolescents (such as noodles, pancakes, scones and other sweet bakery products, colored ice, pizza, etc) and replaced the adult portion sizes with portion sizes suitable for preadolescents. In the FFQ, the participant was asked to indicate for each food item how many times on average they consumed it over the last 7 days. The preadolescents answered the questions themselves, but the caregivers were allowed to help when needed. The FFQ included 174 food items. From the following analyses, we excluded food items used by none ($n = 27$) or only 1 participant ($n = 10$), as well as items we considered unreliably reported ($n = 3$) ([Supplementary Table 1](#)). Hence, we included 135 food items, which were divided into 19 groups ([Supplementary Table 2](#)): refined grains, whole grains, porridges, side dishes (eg, rice, traditional maize porridge called ugali), roots and tubers (eg, cassava, arrowroot and plantain), vegetables (eg, spinach, kales and traditional vegetables), beans, nuts and seeds, fruits, dairy products, meat and eggs, fish and seafood, oils and margarine, spreads and sauces, sweets, savory snacks, sodas and juices, and fast

food (eg, samosa, hot dog, kebab). In addition, coffee and tea were included in the analysis as a group of their own.

In addition to single food groups, we made a whole-diet dietary pattern analysis. The dietary pattern analysis simplifies data and reduces the number of analyses needed and, therefore, helps to control for multiple statistical testing (3 patterns vs 19 food groups). The dietary pattern approach gives additional insight into the diet and helps to identify a bigger picture. Moreover, we compared our results to the most recent larger study, including adolescent participants in Kenya (International Study of Childhood Obesity, Lifestyle and the Environment,) which used dietary pattern analysis. The details of forming the patterns are given in the section on statistical analysis.

Physical activity was measured by an accelerometer (GT3X+, ActiGraph). Accelerometer measurements have been previously validated among Kenyan children.¹⁸ At least 4 valid days (≥ 10 h/d of waking wear time), including 1 weekend day, was required for the participant's data to be included in the accelerometer analysis (104 participants fulfilled this requirement). The data was downloaded onto a computer using an analysis software package (version 6.13, ActiGraph), reviewed for completeness and analyzed using Kinsoft. Using a validated algorithm,¹⁹ nocturnal sleep episodes were removed from the data and nonwear periods were defined as any sequence of at least 20 consecutive minutes of zero activity counts. Evenson cutpoints²⁰ were used to define time spent in sedentary behavior, light, moderate, and vigorous physical activity.

Statistical Analysis

All analyses were conducted using SPSS (version 25, IBM, 2017) and R statistical software (version 3.6.3, R Foundation for Statistical Computing Platform, 2020). Participants' socio-demographic characteristics, BMI, moderate-to-vigorous physical activity (MVPA) and sedentary time, and consumption frequencies of food groups have been described with

mean and SD (continuous variables) or frequencies and percentages (categorical variables).

Our study used principal component analysis (PCA) to create the wealth index and form the DPs. Principal component analysis is a method for reducing dimensions in data (ie, compress the information of multiple variables into fewer variables). It typically includes several iteration rounds that could be described in the following 3 steps: (1) an unrestricted number of components and inspection of the scree plot and Eigenvalues and the Kaiser-Meyer-Olkin test value, (2) restriction of the number of components, and (3) describing the factors by rotated factor loadings. Rotation turns the initial factors into ones that are easier to interpret. Varimax rotation is one of the most used ones. It maximizes the sum of the variance of the squared loadings resulting in a small number of important variables with high factor loadings.

We created the household wealth index following the *World Food Program's* guidelines¹⁵ using PCA (SPSS command FACTOR, Method: Principal components, Varimax rotation). The final wealth index had a Kaiser-Meyer-Olkin value of 0.87, and it explained 40% of the total variation and included: sanitation, floor material, television, refrigerator, chair, cupboard, wall clock, microwave, DVD player, electric or gas stove, kerosene stove, bicycle and car or truck. We grouped the wealth index in quintiles for the analyses. The association between wealth index quintiles and each food group was tested with linear regression. $P < 0.05$ were considered statistically significant, and Bonferroni corrected α for the linear trend test was $0.05/17 = 0.003$.

Principal component analysis is one of the main empirical methods for compressing the food consumption information into pattern scores, which tells how much each participant adheres to the derived DPs. In other words, each participant has a diet that includes stronger or weaker associations with the derived DPs. Initially, we used the 19 food groups (consumption frequencies) in our analysis, which resulted in 3 patterns having at least 5-factor loadings > 0.3

and reaching the Kaiser-Meyer-Olkin test value of 0.66. The percentage of the total variance in explaining food consumption was 36%. We calculated standardized principal component scores for these 3 patterns and each of the preadolescents by assigning weights to their frequency of use of each food. A higher score indicates a stronger adherence to the empirically derived dietary pattern.

We used linear regression to examine the association between sociodemographic (age, sex, parental education, wealth index, BMI z-score) and lifestyle variables (MVPA and sedentary time) with the dietary pattern scores, and $P < 0.05$ were considered statistically significant. Bonferroni corrected α for the association between sociodemographic and lifestyle variables with dietary pattern scores was $0.05/8 = 0.006$.

RESULTS

Table 1 shows that participants in Langata had higher education and wealth than Embakasi Central. We found a statistically significant trend in the consumption frequency by the

wealth index in 9 food groups out of 19 (Table 2). After the Bonferroni correction, the trend remained statistically significant for 6 food groups ($P < 0.003$). All of these indicated higher consumption frequency in the higher wealth index quintiles. The largest proportional difference was seen for sodas and juices (including both sweetened and unsweetened) consumed 8 times more often among adolescents in the highest wealth index quintile compared with the lowest.

In the PCA, 3 DPs were found (Table 3). The first pattern was characterized by food groups often deemed unhealthy, such as snacks, fast food, sodas and juices, and sweets and was thus named the snacks, fast food, and meat pattern. This pattern explained 19% of the variance in food consumption. The second pattern included food groups often considered healthy, such as beans and nuts, dairy, roots and tubers, fish and seafood, whole-grain, and fruits and was named the dairy and plant protein pattern; this explained 8.8% of the variance. The third pattern, named the vegetables

and refined grains pattern, was less diverse than the other 2 and characterized by the intake of rather cheap food items like vegetables, refined grains, oils, and tea, explaining 8.5% of the variance in food consumption.

In the univariate linear regression analysis model for the snacks, fast food, and meat pattern and the dairy and plant protein pattern, parental education and wealth index were positively associated with higher scores (Table 4). In univariate models, none of the examined factors were associated with the vegetables and refined grains pattern scores. In the multivariate analyses, higher wealth and lower sedentary time were associated with higher snacks, fast food and meat pattern scores. After Bonferroni correction, only the association between the wealth index and snacks, fast food and meat pattern remained statistically significant ($P < 0.006$).

DISCUSSION

Consumption of refined cereals, dairy, fruits, meat, spreads, and

Table 1. Characteristics of Preadolescents Residing in Embakasi Central and Langata, in Nairobi City, Kenya

Characteristics	All (n = 149)	Embakasi Central (n = 72) ^a	Langata (n = 77) ^b	P ^c
Mean age, y	11.1 ± 1.50	11.2 ± 1.15	11.2 ± 1.15	0.99
Girls	78 (52)	39 (54.1)	39 (50.1)	0.79
Parental education				< 0.001
No formal education/incomplete primary school	20 (13)	16 (22)	4 (5)	
Primary school	31 (21)	26 (36)	5 (7)	
Secondary school	48 (32)	26 (36)	22 (29)	
Certificate training or adult education	33 (22)	4 (6)	29 (38)	
Tertiary education	17 (11)	0 (0)	17 (22)	
Wealth index fifths,				< 0.001
First (lowest)	30 (20)	30 (42)	0 (0)	
Second	28 (19)	25 (35)	3 (4)	
Third	31 (21)	14 (19)	17 (22)	
Fourth	30 (20)	3 (4)	27 (35)	
Fifth (highest)	30 (20)	0 (0)	30 (39)	
Mean BMI z-score	−0.08 ± 1.49	−0.43 ± 1.25	0.24 ± 1.64	0.007
Mean time spent on MVPA, min/d ^d	71.3 ± 27.7	79.7 ± 30.3	61.2 ± 20.1	< 0.001
Mean time spent on SED, min/d ^d	607.7 ± 78.5	601.0 ± 76.1	615.9 ± 81.3	0.34

BMI indicates body mass index; MVPA, moderate-to-vigorous physical activity; SED, sedentary behavior.

^aEmbakasi Central = low socioeconomic status (SES) area in Nairobi City County; ^bLangata = mid-SES area in Nairobi City County; ^cDifference between areas was tested with analysis of variance for continuous variables and with a chi-square test for categorical variables, $P < 0.05$ were considered statistically significant; ^dAdolescents who wore the accelerometer for at least 4 valid days (≥ 10 h/d of waking wear time), including 1 weekend day (n = 104): Embakasi Central (n = 57) and Langata (n = 47).

Note: Values are presented as mean ± SD or n (%).

Table 2. Frequency of Food Consumption (Times/wk) by Wealth Index Quintiles Among Preadolescents Residing in Nairobi City, Kenya (n = 149)

Food Groups	Wealth Index Quintiles					<i>P</i> ^{a,b}
	Lowest (n = 30)	Second (n = 28)	Third (n = 31)	Fourth (n = 30)	Highest (n = 30)	
White cereals	4.67 ± 2.52	2.96 ± 3.12	4.61 ± 3.95	5.83 ± 2.79	8.17 ± 5.24	< 0.001 ^c
Whole grains	0.67 ± 1.99	0.46 ± 1.40	1.52 ± 1.84	1.57 ± 3.11	1.93 ± 2.18	0.003
Porridges	1.13 ± 2.01	1.93 ± 2.58	1.61 ± 2.40	1.10 ± 1.94	0.83 ± 2.67	0.29
Pasta and rice	7.73 ± 5.51	6.54 ± 4.66	7.74 ± 3.78	7.67 ± 3.45	7.67 ± 3.91	0.71
Roots	0.80 ± 1.75	1.25 ± 2.15	1.06 ± 1.31	1.50 ± 1.50	0.87 ± 1.50	0.63
Beans and nuts	3.97 ± 3.62	3.89 ± 2.88	4.90 ± 3.54	4.67 ± 2.60	4.73 ± 3.34	0.20
Vegetables	14.00 ± 11.50	11.57 ± 11.30	14.00 ± 15.83	9.30 ± 8.02	15.23 ± 13.98	0.92
Fruits	4.17 ± 5.93	4.50 ± 4.22	5.23 ± 4.60	8.67 ± 7.18	8.73 ± 6.98	< 0.001 ^c
Dairy	1.07 ± 1.70	2.25 ± 2.80	2.03 ± 2.81	3.60 ± 4.45	4.63 ± 3.51	< 0.001 ^c
Meat	2.97 ± 2.71	2.46 ± 2.96	3.61 ± 2.79	5.47 ± 3.49	6.53 ± 2.21	< 0.001 ^c
Fish	1.13 ± 1.28	1.11 ± 1.29	0.87 ± 0.96	0.83 ± 1.29	1.10 ± 2.14	0.63
Oils	10.87 ± 6.61	9.39 ± 6.30	11.71 ± 6.92	11.07 ± 6.96	13.63 ± 7.54	0.07
Spreads	0.93 ± 1.70	0.86 ± 2.07	2.81 ± 3.53	2.27 ± 2.63	4.60 ± 3.36	< 0.001 ^c
Sweets	7.00 ± 4.80	6.89 ± 5.44	5.71 ± 3.69	6.17 ± 6.90	5.33 ± 4.11	0.18
Snacks	1.07 ± 2.38	0.79 ± 1.64	1.16 ± 2.05	2.53 ± 3.84	2.40 ± 3.31	0.004
Sugar-sweetened beverages ^d	0.37 ± 0.76	0.64 ± 1.45	1.39 ± 1.93	3.47 ± 4.26	3.23 ± 3.45	< 0.001 ^c
Fast foods	1.80 ± 2.92	2.04 ± 3.10	1.45 ± 1.84	2.43 ± 2.49	3.90 ± 3.10	0.004
Tea	8.37 ± 3.96	6.18 ± 4.18	8.06 ± 3.08	8.57 ± 4.61	7.83 ± 4.64	0.65
Coffee	< 0.01 ± < 0.01	0.07 ± 0.38	< 0.01 ± < 0.01	< 0.01 ± < 0.01	0.47 ± 1.78	0.08

^aTrend between wealth index quintiles and consumption of food groups tested with linear regression; ^bLinear regression analysis for trend was adjusted for participant's age and sex; ^cSignificant after Bonferroni correction ($P < 0.003$); ^dBoth sweetened and unsweetened beverages are included.

Note: Values are presented as mean ± SD.

Table 3. Factor Loadings for Food Groups by Dietary Patterns Identified Through Principal Component Analysis

Food Group	Dietary Patterns		
	Snacks, Fast Food, and Meat	Dairy and Plant Protein	Vegetables and Refined Grains
Savory snacks	0.738 ^a	−0.039	0.107
Fast food	0.725 ^a	0.094	−0.209
Meat and eggs	0.657 ^a	0.317 ^a	0.236
Sodas and juices	0.644 ^a	0.099	0.018
Spreads and sauces	0.525 ^a	0.344 ^a	−0.118
Sweets	0.510 ^a	−0.071	0.085
Coffee	0.330 ^a	−0.051	−0.258
Dairy products	0.231	0.649 ^a	−0.256
Beans and nuts	0.048	0.593 ^a	0.199
Roots and tubers	−0.133	0.572 ^a	0.084
Whole grains	0.068	0.461 ^a	0.003
Side dishes	0.018	0.430 ^a	0.104
Fish and seafood	0.080	0.416 ^a	−0.363 ^a
Fruits	0.401 ^a	0.408 ^a	0.165
Vegetables	−0.036	0.051	0.664 ^a
Tea	0.176	0.032	0.542 ^a
Refined grains	0.437 ^a	0.075	0.500 ^a
Oils and margarine	0.102	0.309 ^a	0.424 ^a
Porridges	−0.110	−0.005	0.176

^aFactor loadings > 0.3.

Table 4. Association Between Sociodemographic Characteristics and Lifestyle With Dietary Pattern Scores

Characteristics	Snacks, Fast Food, and Meat			Dairy and Plant Protein			Vegetables and Refined Grains		
	β	95% CI	P^a	β	95% CI	P^a	β	95% CI	P^a
Univariate model									
Age, y	−0.046	−0.15 to 0.06	0.39	−0.043	−0.15 to 0.06	0.42	−0.015	−0.12 to 0.09	0.77
Sex (reference female)	−0.132	−0.45 to 0.19	0.42	−0.243	−0.56 to 0.08	0.14	−0.094	−0.42 to 0.23	0.57
Parental education	0.179	0.05–0.31	0.009	0.151	0.02–0.28	0.027	0.023	−0.11 to 0.16	0.74
Wealth index	0.398	0.25–0.54	< 0.001 ^b	0.207	0.05–0.36	0.011	0.039	−0.12 to 0.20	0.64
BMI z-score	0.065	−0.05 to 0.13	0.25	−0.014	−0.11 to 0.08	0.78	0.02	−0.09 to 0.13	0.72
MVPA, min/d ^c	−0.006	−0.01 to < 0.01	0.05	−0.004	−0.01 to < 0.01	0.29	0.004	−0.01 to 0.01	0.26
SED, min/d ^c	−0.001	< −0.01 to < 0.01	0.37	< 0.001	< −0.01 to < 0.01	0.72	−0.002	< −0.01 to < 0.01	0.08
Multivariate model ^{c,d}									
Age, y	−0.015	−0.13 to 0.10	0.80	−0.058	−0.19 to 0.08	0.40	0.012	−0.12 to 0.15	0.87
Sex (reference female)	−0.207	−0.53 to 0.12	0.22	−0.252	−0.64 to 0.13	0.20	−0.250	−0.65 to 0.15	0.22
Parental education	−0.115	−0.28 to 0.05	0.18	0.112	−0.08 to 0.31	0.27	0.006	−0.19 to 0.21	0.95
Wealth index	0.392	0.20–0.58	< 0.001 ^b	0.056	−0.17 to 0.28	0.64	0.087	−0.15 to 0.32	0.47
BMI z-score	0.018	−0.10 to 0.14	0.76	0.013	−0.13 to 0.15	0.85	0.039	−0.10 to 0.18	0.60
MVPA, min/d	−0.006	−0.01 to < 0.01	0.14	0.002	−0.01 to 0.01	0.70	0.003	−0.01 to 0.01	0.50
SED, min/d	−0.003	−0.01 to < 0.01	0.04	0.001	< −0.01 to < 0.01	0.43	−0.002	< −0.01 to < 0.01	0.19

BMI indicates body mass index; CI, confidence interval; MVPA, moderate-to-vigorous physical activity; SED, sedentary behavior.

^aAssociation between sociodemographic and lifestyle variables was analyzed with linear regression; ^bStatistically significant after Bonferroni correction ($P < 0.006$); ^cSample size in the analysis was $n = 104$ because of adolescents who wore an accelerometer at least 4 valid days (≥ 10 h/d of waking wear time), including 1 weekend day. Otherwise, the sample size in the analysis was $n = 149$; ^dAll variables simultaneously in the model.

sugar-sweetened beverages was more frequent among preadolescents whose families were wealthier. To get more insight into the underlying dietary habits, we used PCA to reduce the number of dietary variables by creating linear combinations of variables with strong correlations. Three DPs were identified, and they explained 36% of the total variance in preadolescents' food consumption: (1) a pattern high in foods regarded as unhealthy, such as snacks, fast food, sodas and juices, and sweets (snacks, fast food, and meat), (2) a pattern high in foods regarded as healthy, such as beans and nuts, dairy, roots and tubers, fish and seafood, wholegrain, and fruits (dairy and plant protein), and (3) a pattern high in rather cheap foods commonly used in urban areas such as vegetables, refined grains (products made from refined wheat, maize, etc), oils, and tea (vegetables and refined grains). We found higher wealth associated with higher snacks, fast foods, and meat pattern scores.

Previously, the international International Study of Childhood Obesity,

Lifestyle and the Environment research project identified 2 DPs in children aged 9–11 years living in Nairobi: an unhealthy and healthy diet pattern.²¹ These patterns resembled the snacks, fast food, and meat pattern and dairy and plant protein pattern found in this study, although there were some differences; for example, dairy product and fish consumption were lower among our participants. Similar unhealthy and healthy DPs have been identified in other LMIC settings.²² As a part of the lifestyle transition, the availability of snacks and fast foods had increased dramatically since 1990 when supermarket growth started in Kenya.²³ In addition to high availability, unhealthy foods, such as sugar-sweetened beverages, are among the most advertised foods.²⁴ This was reflected in our data as the snacks, fast food, and meat pattern explained most of the variance in food consumption frequency.

In general, higher parental education has been associated with healthy DPs in children in many countries.²⁵ Although we observed that higher parental education was associated

with higher scores of both the snacks, fast food, and meat pattern and the dairy and plant protein pattern in univariate models, these associations disappeared after controlling for wealth index, indicating that wealth probably explains most of the association between parental education and diet. It should also be noted that the above-mentioned unadjusted correlations were found for both unhealthy and healthy patterns. Thus, the findings suggest that the association between education, wealth and diet was more quantitative (participants with higher education consume all foods more frequently) than health-related (participants with higher education would consume only healthy foods more frequently). In middle-SES families, income level allows spending money on beverages, dairy products, nuts and seeds, and meat. Compared with families with the lowest wealth index quintile, the average consumption frequency of all these food groups and variance in consumption was much higher among preadolescents in the highest wealth index

quintile. In summary, despite a marked economic development in Kenya, our results support the evidence that Nairobi, representing an urban area of a new LMIC, would still be in a situation in which higher wealth would be associated with unhealthier DPs.^{2,26}

Moderate-to-vigorous physical activity was not associated with any DPs, but surprisingly, lower sedentary time was associated with a higher snack, fast food, and meat pattern. However, correction for multiple testing indicated that this association must be considered cautiously. Our results do not indicate that healthy thinking would simultaneously drive food consumption and physical activity patterns. Previously, unhealthy diets and high screen time were clustered in Nairobi preadolescents.²⁷ Studies conducted in high-income countries and some in Latin America have observed greater time spent on MVPA to be associated with lower adherence to unhealthy diet patterns.^{28,29} Similarly, many studies have also found greater time spent on MVPA associated with healthy diets.^{30,31}

This study includes limitations. As already mentioned, the sample size was limited ($n = 149$). Analyses, including accelerometer data, suffered more than the other analyses (multivariate analysis in Table 4; $n = 104$) because of the high prevalence of unacceptable data collection and missing data. The main reason for the limited sample size is that the whole project includes an in-depth analysis of the participants, with numerous analyses and questionnaires. We aimed to get a deep understanding of a specific population, not a superficial overview of a larger group.

The cross-sectional design of the study does not allow inferences of causality, and without proper previous reference data, no valid assessment of change can be made. We conducted multiple exploratory analyses using various variables, and thus, the results found may, to some degree, be attributed to chance. However, correction for multiple testing did not change the interpretation of the results remarkably. Furthermore, methodological refinement would help provide more detailed insight

into the validity of the FFQ and prompt greater adherence to wear time for accelerometers.

Although we acknowledge limitations, there were also strengths to this work. For example, the selection of 2 study areas that differed by the wealth index provided novel insights into the understanding of lifestyle behaviors of boys and girls in low- and middle-SES families in an urban setting in a lower middle-income economy. The background questionnaire used for assessing participants' sociodemographic background has been validated in the Kenyan context, and we followed standardized methods for constructing the wealth index. The FFQ used was extensive and thus likely to capture the true food consumption patterns. In addition, FFQ makes it possible to assess the habitual intake of foods, which reduces the day-to-day variation in data.³² For physical activity data, device-based measurement is not prone to self-report bias and allows the detection of different intensities and sedentary time. As research on the association between sociodemographic and lifestyle factors and diet is lacking in Africa and LMICs, this study provided initial indicators of the associations between wealth status, geographic location, and lifestyle behaviors in Kenyan adolescents.

IMPLICATIONS FOR RESEARCH AND PRACTICE

Wealth showed the strongest association with a dietary pattern characterized by food groups often deemed unhealthy, such as sodas, juices, and sweets. Based on our observation, the dietary habits of preadolescents living in the urban environment of Nairobi, Kenya—which was upgraded as an LMIC < 10 years ago—do not yet resemble high-income countries in which preadolescents from less wealthy families would have unhealthier diets compared with preadolescents from wealthier families.

As > 90% of existing epidemiological evidence and almost all interventions have been carried out in high-income countries, actions are

warranted to investigate what works for promoting a healthy lifestyle in the context of low- and middle-income countries.^{33–35} Furthermore, whether interventions promoting healthy lifestyles reduce social inequalities in health in low- and middle-income countries remains uncertain.^{36,37} As these countries are still in an early phase of their lifestyle transition, the expansion of obesity to epidemic proportions may be prevented if the correct actions are known and taken shortly.

A useful approach for health promotion through social support in an LMIC setting is the use of peer counselors or lay health educators, also known as CHVs.³⁸ The CHVs are an established network of community members to whom other community members turn for care, advice, information, and support. In Kenya, the naturally occurring social network of CHVs is indigenous to the community and offers culturally relevant and effective social support. CHVs belong to community health units responsible for making weekly home visits to households within designated geographical areas.³⁸ The Mobile Health (mHealth) approach has the potential to bridge systemic gaps needed to improve access to and use of health services, particularly among underserved populations.^{39,40} Mobile Health interventions are rapidly gaining popularity for their potential to improve public health, and many low and LMICs see them as an important resource for frontline health workers. Most CHV and mHealth programs in developing countries have focused on reproductive health (including family planning), maternal child health (promoting breastfeeding), and infectious and vectorborne diseases.^{40,41} However, the potential of using CHVs and mHealth to facilitate change in lifestyle behaviors in this context could be examined. Along with CHVs, Kenya provides a great opportunity to use mHealth: mobile phone coverage has increased rapidly and is currently > 100% per 100 inhabitants and 82% in Africa.⁴² Mobile Health has been widely exploited in Kenya as the country has one of the highest reported mHealth projects globally.⁴⁰

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SUPPLEMENTARY DATA

Supplementary data related to this article can be found at <https://doi.org/10.1016/j.jneb.2023.02.001>.

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