*Research Article*

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

Noora Kanerva, PhD[1]; Lucy Joy Wachira, PhD[2]; Noora Uusi-Ranta, MS[1]; Esther L. Anono, BS[3]; Hanna M. Walsh[1]; Maijaliisa Erkkola, PhD[1]; Sophie Ochola, PhD[3]; Nils Swindell, PhD[4]; Jatta Salmela, PhD[5]; Henna Vepsäläinen, PhD[1]; Gareth Stratton, PhD[6]; Vincent Onywera, PhD[2]; Mikael Fogelholm, PhD[1]

## 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.)

Accepted February 6, 2023.

## INTRODUCTION

The increase in obesity in lower-middle-income countries (LMICs) is largely thought to be affected by lifestyle 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 settings[4] 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

[1]Department of Food and Nutrition, University of Helsinki, Helsinki, Finland
[2]Department of Physical Education, Exercise and Sports Science, Kenyatta University, Nairobi, Kenya
[3]Department of Food, Nutrition and Dietetics, Kenyatta University, Nairobi, Kenya
[4]Department of Sport Sciences, Swansea University, Swansea, United Kingdom
[5]Department of Public Health, University of Helsinki, Helsinki, Finland
[6]Department of Paediatric Exercise Science, Sport and Exercise Sciences, Swansea University, Swansea, United Kingdom

*Conflict of Interest Disclosure:* The authors have not stated any conflicts of interest.

Address for correspondence: Noora Kanerva, PhD, Department of Food and Nutrition, University of Helsinki, Agnes Sjöbergin katu 2, Helsinki 00014, Finland; E-mail: noora.kanerva@helsinki.fi



https://doi.org/10.1016/j.jneb.2023.02.001

changing from traditional staple foods toward refined grains, especially in urban environments[7] 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 timepoint 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, $\alpha$ 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 Surveys[14] 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 Kinesoft. 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 cutpoints[20] 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' sociodemographic 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* guidelines[15] using PCA (SPSS command FACTOR, Method: Principal components, Varimax rotation). The final wealth index had a Kaiser-Mayer-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 $\alpha$ 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 $\alpha$ 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, wholegrain, 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.
[a]Embakasi Central = low socioeconomic status (SES) area in Nairobi City County; [b]Langata = mid-SES area in Nairobi City County; [c]Difference 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; [d]Adolescents 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)

| | Wealth Index Quintiles | | | | | |
|---|---|---|---|---|---|---|
| **Food Groups** | **Lowest (n = 30)** | **Second (n = 28)** | **Third (n = 31)** | **Fourth (n = 30)** | **Highest (n = 30)** | **$P$[a,b]** |
| 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 |

[a]Trend between wealth index quintiles and consumption of food groups tested with linear regression; [b]Linear regression analysis for trend was adjusted for participant's age and sex; [c]Significant after Bonferroni correction ($P < 0.003$); [d]Both 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

| | Dietary Patterns | | |
|---|---|---|---|
| **Food Group** | **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 |

[a]Factor loadings > 0.3.

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

| | Snacks, Fast Food, and Meat | | | Dairy and Plant Protein | | | Vegetables and Refined Grains | | |
|---|---|---|---|---|---|---|---|---|---|
| **Characteristics** | **ß** | **95% CI** | ***P*[a]** | **ß** | **95% CI** | ***P*[a]** | **ß** | **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.
[a]Association between sociodemographic and lifestyle variables was analyzed with linear regression; [b]Statistically significant after Bonferroni correction ($P < 0.006$); [c]Sample 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; [d]All 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 Nairobian 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]

## ACKNOWLEDGMENTS

The Kenya-Finland Education and Research Alliance project is funded by the Finnish Ministry of Foreign Affairs through the Higher Education Institutions Institutional Cooperation Instrument (Higher Education Institutions Institutional Cooperation Instrument; grant no. HEL7M0453-82). The authors would like to thank Elisa Särkilahti (University of Helsinki), who did her master's thesis on the DPs within this project. The authors also want to thank Victor Okoth Odhiambo (Kenyatta University), the Kenya-Finland Education and Research Alliance project coordinator, who gave a lot of general support during the study to the students from Kenyatta University who participated in data collection. Our warmest thanks also go to the health officers and CHVs who helped collect data. Finally, the authors want to thank the families who took part in our study and the communities of Langata and Embakasi Central for their acceptance and contribution.

## SUPPLEMENTARY DATA

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

## REFERENCES

1. Jaacks LM, Vandevijvere S, Pan A, et al. The obesity transition: stages of the global epidemic. *Lancet Diabetes Endocrinol*. 2019;7:231–240.
2. Hosseinpoor AR, Bergen N, Kunst A, et al. Socioeconomic inequalities in risk factors for non communicable diseases in low-income and middle-income countries: results from the World Health Survey. *BMC Public Health*. 2012;12:912.
3. Neupane S, Prakash KC, Doku DT. Overweight and obesity among women: analysis of demographic and health survey data from 32 Sub-Saharan African Countries. *BMC Public Health*. 2016;16:30.
4. Kimani-Murage EW, Muthuri SK, Oti SO, Mutua MK, van de Vijver S, Kyobutungi C. Evidence of a double burden of malnutrition in urban poor settings in Nairobi, Kenya. *PLoS One*. 2015;10:e0129943.
5. Christensen DL, Eis J, Hansen AW, et al. Obesity and regional fat distribution in Kenyan populations: impact of ethnicity and urbanization. *Ann Hum Biol*. 2008;35:232–249.
6. Wachira LJ, Muthuri S, Ochola S, Onywera V, Tremblay M. Association between dietary behaviours and weight status of school children: results from the International Study of Childhood Obesity, Lifestyle and the Environment (ISCOLE) - Kenya. *Child and Adolescent Obesity*. 2021;4:1–22.
7. Oniang'o RK, Mutuku JM, Malaba SJ. Contemporary African food habits and their nutritional and health implications. *Asia Pac J Clin Nutr*. 2003;12:331–336.
8. Steyn NP, Nel JH, Parker WA, Ayah R, Mbithe D. Dietary, social, and environmental determinants of obesity in Kenyan women. *Scand J Public Health*. 2011;39:88–97.
9. Mbochi RW, Kuria E, Kimiywe J, Ochola S, Steyn NP. Predictors of overweight and obesity in adult women in Nairobi Province, Kenya. *BMC Public Health*. 2012;12:823.
10. Kigaru DMD, Loechl C, Moleah T, Macharia-Mutie CW, Ndungu ZW. Nutrition knowledge, attitude and practices among urban primary school children in Nairobi City, Kenya: a KAP study. *BMC Nutr*. 2015;1:44.
11. Onywera VO, Adamo KB, Sheel AW, Waudo JN, Boit MK, Tremblay M. Emerging evidence of the physical activity transition in Kenya. *J Phys Act Health*. 2012;9:554–562.
12. Broyles ST, Denstel KD, Church TS, et al. The epidemiological transition and the global childhood obesity epidemic. *Int J Obes Suppl*. 2015;5(suppl 2):S3–S8.
13. Hartung C, Lerer A, Anokwa Y, Tseng C, Brunette W, Borriello G. Open data kit: tools to build information services for developing regions. In: *Proceedings of the 4th ACM/IEEE International Conference on Information and Communication Technologies and Development - ICTD '10*. ACM Press; 2010:1–12.
14. Kenya National Bureau of Statistics, Ministry of Health, National AIDS Control Council, Kenya Medical Research Institute, National Council for Population and Development. *Kenya: Demographic and Health Survey 2014*. Kenya National Bureau of Statistics; 2015. http://publications.universalhealth2030.org/uploads/kenya_-demographic_and_health_survey_2014.pdf. Accessed October 13, 2022.
15. Hjelm L, Miller D, Wadhwa A. *VAM Guidance Paper. Creation of Wealth Index*. World Food Programme; 2017. https://docs.wfp.org/api/documents/WFP-0000022418/download/. Accessed October 13, 2022.
16. de Onis M, Onyango AW, Borghi E, Siyam A, Nishida C, Siekmann J. Development of a WHO growth reference for school-aged children and adolescents. *Bull World Health Organ*. 2007;85:660–667.
17. Vila-Real C, Pimenta-Martins A, Magu JS, et al. A culture-sensitive semi-quantitative FFQ for use among the adult population in Nairobi, Kenya: development, validity and reproducibility. *Public Health Nutr*. 2021;24:834–844.
18. Barreira TV, Schuna JM, Tudor-Locke C, et al. Reliability of accelerometer-determined physical activity and sedentary behavior in school-aged children: a 12-country study. *Int J Obes Suppl*. 2015;5(suppl 2):S29–S35.
19. Tudor-Locke C, Barreira TV, Schuna JM, Mire EF, Katzmarzyk PT. Fully automated waist-worn accelerometer algorithm for detecting children's sleep-period time separate from 24-h physical activity or sedentary behaviors. *Appl Physiol Nutr Metab*. 2014;39:53–57.
20. Trost SG, Loprinzi PD, Moore R, Pfeiffer KA. Comparison of accelerometer cut points for predicting activity intensity in youth. *Med Sci Sports Exerc*. 2011;43:1360–1368.
21. Mikkilä V, Vepsäläinen H, Saloheimo T, et al. An international comparison of dietary patterns in 9−11-year-old children. *Int J Obes Suppl*. 2015;5(suppl 2). S17−21.
22. Pinho Ld de, Silveira MF, Botelho ACde C, Caldeira AP. Identification of dietary patterns of adolescents attending public schools. *J Pediatr (Rio J)*. 2014;90:267–272.
23. Rischke R, Kimenju SC, Klasen S, Qaim M. Supermarkets and food consumption patterns: the case of small towns in Kenya. *Food Policy*. 2015;52:9–21.
24. Green MA, Pradeilles R, Laar A, et al. Investigating foods and beverages sold

and advertised in deprived urban neighbourhoods in Ghana and Kenya: a cross-sectional study. *BMJ Open*. 2020;10:e035680.
25. Manyanga T, Tremblay MS, Chaput JP, et al. Socioeconomic status and dietary patterns in children from around the world: different associations by levels of country human development? *BMC Public Health*. 2017;17:457.
26. Mayén AL, Marques-Vidal P, Paccaud F, Bovet P, Stringhini S. Socioeconomic determinants of dietary patterns in low- and middle-income countries: a systematic review. *Am J Clin Nutr*. 2014;100:1520–1531.
27. Dumuid D, Olds T, Lewis LK, et al. Health-related quality of life and lifestyle behavior clusters in school-aged children from 12 countries. *J Pediatr*. 2017;183:178−183.e2.
28. Sabbe D, De Bourdeaudhuij I, Legiest E, Maes L. A cluster-analytical approach towards physical activity and eating habits among 10-year-old children. *Health Educ Res*. 2008;23:753–762.
29. Cabanas-Sánchez V, Martínez-Gómez D, Izquierdo-Gómez R, Segura-Jiménez V, Castro-Piñero J, Veiga OL. Association between clustering of lifestyle behaviors and health-related physical fitness in youth: the UP&DOWN study. *J Pediatr*. 2018;199:41−48.e1.
30. Yannakoulia M, Lykou A, Kastorini CM, et al. Socio-economic and lifestyle parameters associated with diet quality of children and adolescents using classification and regression tree analysis: the DIATROFI study. *Public Health Nutr*. 2016;19:339–347.
31. Tambalis KD, Panagiotakos DB, Psarra G, Sidossis LS. Concomitant associations between lifestyle characteristics and physical activity status in children and adolescents. *J Res Health Sci*. 2019;19:e00439.
32. Willett WC. Food frequency methods. In: Willett WC, ed. *Nutritional Epidemiology*, 3rd ed., Oxford University Press; 2013. p. 70.
33. Allen LN, Pullar J, Wickramasinghe KK, et al. Evaluation of research on interventions aligned to WHO "Best Buys" for NCDs in low-income and lower-middle-income countries: a systematic review from 1990 to 2015. *BMJ Glob Health*. 2018;3:e000535.
34. Mead E, Brown T, Rees K, et al. Diet, physical activity and behavioural interventions for the treatment of overweight or obese children from the age of 6 to 11 years. *Cochrane Database Syst Rev*. 2017;6:CD012651.
35. Allen LN, Fox N, Ambrose A. Quantifying research output on poverty and non-communicable disease behavioural risk factors in low-income and lower middle-income countries: a bibliometric analysis. *BMJ Open*. 2017;7:e014715.
36. Mayén AL, de Mestral C, Zamora G, et al. Interventions promoting healthy eating as a tool for reducing social inequalities in diet in low- and middle-income countries: a systematic review. *Int J Equity Health*. 2016;15:205.
37. Pullar J, Allen L, Townsend N, et al. The impact of poverty reduction and development interventions on non-communicable diseases and their behavioural risk factors in low and lower-middle income countries: a systematic review. *PLoS One*. 2018;13:e0193378.
38. Otieno CF, Kaseje D, Ochieng' BM, Githae MN. Reliability of community health worker collected data for planning and policy in a peri-urban area of Kisumu, Kenya. *J Community Health*. 2012;37:48–53.
39. Agarwal S, Perry HB, Long LA, Labrique AB. Evidence on feasibility and effective use of mHealth strategies by frontline health workers in developing countries: systematic review. *Trop Med Int Health*. 2015;20:1003–1014.
40. Agarwal S, Rosenblum L, Goldschmidt T, Carras M, Goal N, Labrique AB. *Mobile Technology in Support of Frontline Health Workers: A Comprehensive Overview of the Landscape, Knowledge Gaps and Future Directions*. Global mHealth Initiative. Johns Hopkins University; 2016. https://chwcentral.org/wp-content/uploads/2016/11/Mobile-Technology-in-Support-of-Frontline-Health-Workers.pdf. Accessed October 13, 2022.
41. Goudet S, Griffiths PL, Wainaina CW, et al. Social value of a nutritional counselling and support program for breastfeeding in urban poor settings, Nairobi. *BMC Public Health*. 2018;18:424.
42. International Telecommunication Union. *Mobile Cellular Subscriptions 2000−2021*. ICT Statistics; 2021. https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx. Accessed October 13, 2022.

## ORCIDs

Noora Kanerva: http://orcid.org/0000-0001-6776-9357
Lucy Joy Wachira: http://orcid.org/0000-0003-2805-5997
Hanna M. Walsh: http://orcid.org/0000-0002-4923-2991
Nils Swindell: http://orcid.org/0000-0003-3742-6139
Jatta Salmela: http://orcid.org/0000-0001-7880-834X
Gareth Stratton: http://orcid.org/0000-0001-5618-0803
Vincent Onywera: http://orcid.org/0000-0001-8351-4696
Mikael Fogelholm: http://orcid.org/0000-0001-8110-102X