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Validation of Mobile Artificial Intelligence Technology–Assisted Dietary Assessment Tool Against Weighed Records and 24-Hour Recall in Adolescent Females in Ghana

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A B S T R A C T

Background: Important gaps exist in the dietary intake of adolescents in low- and middle-income countries (LMICs), partly due to expensive assessment methods and inaccuracy in portion-size estimation. Dietary assessment tools leveraging mobile technologies exist but only a few have been validated in LMICs.
Objective: We validated Food Recognition Assistance and Nudging Insights (FRANI), a mobile artificial intelligence (AI) dietary assessment application in adolescent females aged 12–18 y ($n = 36$) in Ghana, against weighed records (WR), and multipass 24-hour recalls (24HR).
Methods: Dietary intake was assessed during 3 nonconsecutive days using FRANI, WRs, and 24HRs. Equivalence of nutrient intake was tested using mixed-effect models adjusted for repeated measures, by comparing ratios (FRANI/WR and 24HR/WR) with equivalence margins at 10%, 15%, and 20% error bounds. Agreement between methods was assessed using the concordance correlation coefficient (CCC).
Results: Equivalence for FRANI and WR was determined at the 10% bound for energy intake, 15% for 5 nutrients (iron, zinc, folate, niacin, and vitamin B6), and 20% for protein, calcium, riboflavin, and thiamine intakes. Comparisons between 24HR and WR estimated equivalence at the 20% bound for energy, carbohydrate, fiber, calcium, thiamine, and vitamin A intakes. The CCCs by nutrient between FRANI and WR ranged between 0.30 and 0.68, which was similar for CCC between 24HR and WR (ranging between 0.38 and 0.67). Comparisons of food consumption episodes from FRANI and WR found 31% omission and 16% intrusion errors. Omission and intrusion errors were lower when comparing 24HR with WR (21% and 13%, respectively).
Conclusions: FRANI AI–assisted dietary assessment could accurately estimate nutrient intake in adolescent females compared with WR in urban Ghana. FRANI estimates were at least as accurate as those provided through 24HR. Further improvements in food recognition and portion estimation in FRANI could reduce errors and improve overall nutrient intake estimations.

Keywords: adolescent, diet, dietary assessment tools, dietary intake assessment, dietary methods, low-income countries, validation

Abbreviations: AI, artificial intelligence; CCC, concordance correlation coefficient; EAR, estimated average requirement; FRANI, Food Recognition Assistance and Nudging Insights; IOM, Institute of Medicine; LIMC, low- and middle-income countries; LOA, limits of agreement; MPA, mean probability of adequacy; WR, weighed records; 24HR, 24-hour recall.

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Introduction

Dietary risk factors are estimated to cause 11 million deaths and 255 million disability-adjusted life-years yearly [1]. Although insufficient nutrient intakes are the key risk factors for undernutrition [2], rapid increases in unhealthy diets, coupled with reductions in physical activity have contributed to increases in rates of overweight and obesity [3]. Malnutrition during childhood and adolescence is associated with psychosocial problems, social stigmatization, poor self-image [4], non-communicable diseases in adulthood [5–7], and reduced life expectancy [8,9]. Adolescence is also a time when habits are formed when youth start making their own decisions and are particularly sensitive and selective about information sources for decisions. Despite these challenges, there are no global nutrition targets for adolescents, and adolescent nutrition has been mostly overlooked in interventions and policies [10]. Female adolescents are of particular interest because in many low- and middle-income countries, the double burden of malnutrition is high in this group, leading to poor health outcomes for the adolescent, which are passed on to the next generation [11].

Data on food and nutrient consumption are essential to inform nutrition policies and programs. However, there are important gaps in the data on diets in low- and middle-income countries (LIMCs), particularly for adolescents [12,13]. Quantitative dietary intake data collection and analysis are complex and expensive. Survey-based dietary assessment commonly involves the multipass 24-hour recall (24HR) method that has been validated in LMICs for adults reporting their intake and that of their young children and adolescents [14]. In children and adolescents, however, the accuracy of self-reported food intake without caregiver assistance is not clear. Several subject- and assessment-related constraints have been identified, including the ability and willingness to self-report food consumption, and the higher variability in their daily nutrient intakes compared with adults [15]. From a costing perspective, undertaking multipass 24HR requires substantial financial investments of the order of $60–$100 per person recall [16].

To address gaps in dietary assessment methods, mobile phone–assisted dietary assessment tools have been proposed in some studies, but existing tools are constrained by a lack of assessments of validity and feasibility of use in LMIC, including in adolescents [17]. Nudging for Good (NFG) is an innovation aimed at developing, validating, and examining the feasibility of using AI mobile technology to provide real-time diagnostics and tailored "nudging" as a strategy to improve the diets and nutrition of adolescent females living in urban Ghana and Vietnam [18]. The NFG project design has 3 main stages. The first stage had 3 components: preparing the food inventory, taking pictures of the foods we cooked, and finally annotating these pictures. In the second stage, semantic segmentation models were trained to recognize foods and estimate portion sizes using the annotated images from the first stage. Finally, the Food Recognition Assistance and Nudging Insights (FRANI) mobile application was developed. This involved *1*) conducting 2 rounds of focus group discussions with potential users to develop the front-end user interface; and *2*) developing an Android-based mobile phone application integrating the user interface with the AI model and back-end databases.

This study aimed to validate FRANI, which is the new mobile AI application for dietary assessment in adolescent females aged 12–18 y in Ghana against the gold standard of observed weighed records (WR) and compare the accuracy of FRANI with the 24HR method. Specifically, the study objectives were *1*) to estimate nutrient intake and adequacy of micronutrient intake using the 3 methods; *2*) to assess the equivalence bounds and extent of agreement of FRANI with WR and 24HR methods; and *3*) to examine the sources of error (memory, omission, intrusion, and portion estimation) for FRANI and 24HR methods.

Methods

Study population

The intervention targeted 10 urban communities that were involved in the Accra Urban Adolescent Nutrition Study in Ghana (NMIMR-IRB Study Number 022–19–20). The Accra Urban Adolescent Nutrition Study employed purposive sampling according to socioeconomic profile of neighborhoods to provide a mix of different food environments and included a total of 10 neighborhoods: 5 neighborhoods were randomly selected from the list of neighborhoods belonging to the lowest tertile of housing (representing the poorest neighborhoods) using the quality/slum index [19,20] and 5 neighborhoods selected from the highest tertile of housing quality/slum index (representing better-off neighborhoods). The 10 neighborhoods included Abelenkpe, Accra New Town, Achimota, Kokomlemle, New Mamprobi, Nungua Old Town, Chorkor, South Industrial Area, South La Estates, and West Legon Residential (Supplemental Figure 2). A random sample of households with at least 1 adolescent girl in the target age range was drawn using the census lists compiled by the Accra Urban Adolescent Nutrition Study team.

Sample size

For this study, a sample of 36 adolescent girls aged 12–18 y were purposively drawn for representation from different socioeconomic classes from the Accra Urban Adolescent Nutrition Study. For logistical reasons, 5 out of the 10 locations were purposively selected and participants were randomly drawn as follows: Achimota (9), Kokomlemle (5), Nungua (5), West Legon (6), and Chorkor (6). Participants were predominantly of low socioeconomic status. Hence a further purposive selection was made of 5 participants from Korle-Bu, a higher socioeconomic area.

The sample size was based on the ability to detect a 10% difference in energy intake estimated using the different dietary assessment methods and detecting equivalence within 10% bounds, as shown in a validation study in a similar study population [18]. We also aimed to assess whether the different methods were equivalent and recalculated the bound we could detect equivalence for given our sample size and actual mean and SD of energy intakes by weighed record, and our sample size was sufficient to detect a difference in energy intake within a 13% bound (alpha = 0.05, beta = 20%).

Validation studies in the literature have suggested using equivalence bounds of 10% or 15% of the difference between methods as reasonable for nutrient intake comparisons [21,22], although 1 dietary intake validation study has used a bound of 20% [23] Following Arsenault et al. [14] and Nguyen et al. [24], given uncertainties about what the acceptable bound should be, and what could be detected with our sample size, we also considered bounds of 15% and 20%, which have been used in other dietary validation contexts [21]. It is important to note that the same criteria for equivalence margins (or bounds) were used across all the nutrients. In addition to using equivalence bounds, we also used the concordance correlation coefficient (CCC) to assess the extent of agreement in nutrient intake estimates across the assessment methods [25]. This approach follows our validation study in Vietnam [24].

Data collection

Dietary intake was assessed on 3 nonconsecutive days, including 2 weekdays and a weekend day for each of the 3 dietary assessment methods, while ensuring that the reference day was the same for each method. For example, on the first weekday visit, trained enumerators visited the participant early in the morning to handover the mobile phone application and then began the WR including all foods and beverages consumed. On the following day, a different enumerator undertook a multipass 24HR with the same participant. Data collection for WR and FRANI application thus took place simultaneously on each reference day, whereas the 24HR was completed the subsequent day using the previous day as a reference. A team of 14 enumerators and 2 supervisors who had nutrition or health-related backgrounds and previous experience in dietary data collection were trained over 13 d, using lectures, role play, mock interviews, and field practice methods. Training to administer the 24HR multipass questionnaire included prompting for frequently forgotten foods. All data were checked daily by supervisors for completeness and accuracy.

Informed consent was requested from each of the participants using a standardized form. Consent/accent for adolescent girls was provided by themselves, and parental consent was obtained from their parents or legal guardians. Ethical clearance was obtained from IFPRI IRB and Noguchi IRB. (Federal-wide Assurance, FWA, number 00001824, NMIMR IRB CPN 078/19–20).

Food Recognition Assistance and Nudging Insights

Thirty-six standard android mobile phones (Samsung Galaxy A21s) were preloaded with preconfigured AI-app and provided to participants during a prespecified 7-d period. Participants were trained and instructed to take images of the foods and beverages consumed at every meal, or instance of food consumption, using the FRANI mobile application. Users would take a picture of the meal they were about to consume, confirm the classification of food returned by FRANI and input the amount of actual food consumed as a proportion of the total portion served. When food classification returned by FRANI was not accurate or complete, users could record the particular food item consumed by selecting the appropriate item from a comprehensive list of foods consumed in Accra compiled from previous studies. To facilitate portion-size estimation, a "pop-socket" was used as a standardized visual prop. A pop-socket is a small disk of standard size (diameter = 4 cm) that participants placed next to food items when taking the picture of the food they were about to consume. FRANI food recognition incorporates an algorithm designed to adjust each pixel in the respective images using the pop-socket reference to estimate the 2-dimensional area covered by each food in the image and then estimate the weight in grams based on that area.

Observed weighed records

Trained enumerators monitored participants from early morning until after their last evening meal, recording the weights of foods and liquids consumed chronologically. Enumerators verified whether any meals were consumed before their arrival. If a meal had been eaten before the enumerator's arrival, an alternative quantification method was used through recall. When a mixed dish was consumed, enumerators recorded details of the recipe, including the weights of the individual ingredients in the dish, the final weight of the cooked mixed dish, and the weight consumed by the individual. Details of recipes were provided by the household member who cooked the meals. If a food item involved residual waste (bones, skin, and others), the enumerators recorded the weight of the waste. Enumerators confirmed that participants had eaten their last meal of the day before departing in the evening.

24-Hour recalls

Dietary data for the 24HR survey was collected using an adaptation of the interactive, multipass quantitative 24HR recall method [26]. The method involves interviewing participants and listing all foods and liquids consumed individually, as well as listing separately ingredients consumed as components of recipes. All foods and liquids were recorded regardless of quantities consumed, including condiments. Interviews were conducted with the use of visual aids to assist in estimating portion sizes. A preferred method was established for each food, including direct weighing of substitutes similar in nature to the consumed foods. Dry powdery foods were estimated with "gari," a dry powdery food made by pan-roasting of grated cassava. In some cases, household handy measures and calibrated portion-size models were used to estimate weights of cooked grains, roots, and tubers. Volumes of liquid/semi-solid foods such as soups, sauces, and porridges were estimated with water. Some items were estimated by price.

During data collection, all data were checked daily by the supervisor, research assistants, and Principal Investigator, for consistency and plausibility. Queries were followed up with respondents for clarification within 48 h. Food density values and household measure weights were used to convert quantity data collected from volume or household measures into grams. Conversion factors were applied to calculate the weights of the items that were estimated by household measures, food models, and water. Conversion factors and recipe information were collected before the dietary assessment. Weights of items estimated by price were obtained by buying and weighing them. All data entry was checked for completeness and accuracy by 3 members of the research team.

Estimating food and nutrient intakes

For the 3 different methods, quantities in grams of different food items that participants had consumed over the past 24 h were converted into nutrients using several food-composition tables adapted to local Ghanaian foods. Nutrient composition data were obtained from the West African food-composition table [27] and the RING nutrient composition table [28], which is a compilation of food-composition databases relevant to Ghana. The computation of nutrients was done using a program written in Stata. All micronutrients were expressed in micrograms and milligrams except vitamin A, which was expressed in micrograms of retinol activity equivalents (RAE). For each micronutrient, we calculated the probability of adequacy of intake using the estimated average requirements (EAR) and SD from the European Food Safety Authority (EFSA) recommendations [29]. For vitamin B-12, as the EFSA recommendations only provide the adequate intake reference values, the adequacy ratio was calculated as the ratio between the actual intake and the adequate intake reference value, capped at 1 when the actual intake was higher than the adequate intake reference value. The mean probability of adequacy (MPA) was calculated by averaging the probability of adequacy (or Adequacy Ratios for B-12) values across the 11 micronutrients considered. The dietary data were used to also assess intakes of different food groups and measure dietary diversity of individuals. Each individual food was classified into a food group based on the Minimum Dietary Diversity for Women (MDD-W) guidelines whose food groups include: *1*) grains, white roots and tubers, and plantains; *2*) pulses; *3*) nuts and seeds; *4*) dairy; *5*) flesh foods; *6*) eggs; *7*) dark green leafy vegetables; *8*) vitamin A-rich fruits and vegetables; *9*) other vegetables; and *10*) other fruits [30]. This classification was shown to provide a food group score that is an adequate proxy of the MPA of nonpregnant and nonlactating women of reproductive age. Oils (except vitamin A-enriched oils and red palm oil), drinks, and condiments were not classified into food groups. Foods whose total consumption during the day was less than 10 g were considered condiments.

Statistical analysis

Bland–Altman plots were used to depict the individual differences in energy intake for each method (recall minus observed) versus the average energy intake by the 2 methods. The limits of agreement were calculated as the mean difference ± 1.96 standard deviations, and limits of agreement lines were examined visually.

Nutrient intakes were tested for normality, and log-transformed values were used for statistical testing. We presented descriptive statistics only on nutrient intakes for ease of interpretation. Validation of FRANI against WRs and comparisons with 24HR was undertaken using equivalence testing of mean differences of log-transformed nutrient intakes using 10%, 15%, and 20% equivalence bounds [14] using mixed-effect models to account for the repeated measures. In addition, we examined the extent of agreement between FRANI and WR, and between 24HR and WR using the CCC also adjusted for repeated measures [31].

Errors in portion estimation were assessed by comparing the reported food amounts by 24HR to the observed amounts by WR for the most commonly consumed foods. We considered foods that had at least 60 consumption episodes across all children that were present in both WR and 24HR, as this captured most frequently consumed foods.

Results

Complete recalls were obtained for a total of 99 person-days out of the planned 108. This was due to challenges related to the upload of images on FRANI due to 3G network availability, resulting in the inability to reconcile the images to the reference period in the WR assessment. As such, data from 9 person-days were excluded from the analysis.

Descriptive statistics

Adolescent female participants were 16.5 y old on average (Table 1). All but 1 participant (3%) had completed primary school, 38% had completed junior high school, and 16% had completed senior high school. Participants lived in households of 4 people on average, with all households owning a mobile phone, more than 85% of households had access to electricity and owned a TV, and 62% owned a refrigerator. Mean daily energy intakes were 1844, 1898, and 2066 kcals/d for WR, FRANI application, and 24HR, respectively (Table 2). The

TABLE 1
Characteristics of adolescents ($n = 36$)

Characteristics (household)	Mean (SD)/%	Characteristics (adolescents))	Mean (SD)/%
Number of people in household, n	4.2 (1.8)	Age (y)	16.5 (1.7)
Proportion of households owning assets:		Highest education level completed:	
Mobile phone	100.0	Preschool	2.7
Bed	89.2	Primary school	43.2
Electricity	89.2	Junior High	37.8
TV	86.5	Senior High	16.2
Refrigerator	62.2	Most recent math exam score (0–100)	55.4 (20.7)
Radio	56.8	Most recent English exam score (0–100)	62.6 (16.7)
Wall clock	35.1		
Sewing machine	21.6		
Computer/Tablet computer	16.2		
Freezer	16.2		
Video deck/DVD/VCD	10.8		
Washing machine	8.1		
HH head's highest education level completed			
Preschool	3.9		
Primary school	15.4		
Junior High	46.2		
Senior High	26.9		
Tertiary education	7.7		

TABLE 2
Nutrient intakes of adolescents over 3 d of observed weighed records, FRANI app and 24-h recall

Nutrient intake per person day	WR (n = 99)[1]		FRANI (n = 99)[1]		24HR (n = 99)[1]	
	Mean (SD)	Median (IQR)	Mean (SD)	Median (IQR)	Mean (SD)	Median (IQR)
Energy, kcal	1844 (797)	1770 (1002)	1898 (938)	1680 (1304)	2066 (873)	1996 (1230)
Protein, g	49.8 (25.7)	43.7 (31.8)	56.6 (31.5)	51.2 (48)	60.3 (29.5)	55.5 (39.4)
Fat, g	83.1 (58.2)	70.2 (70.1)	97.9 (70.3)	68.5 (99)	95.7 (64.3)	74.4 (87.2)
Carbohydrate, g	187 (81.2)	181.1 (91.2)	175.1 (96.3)	147.5 (101.7)	202.4 (107.9)	173.9 (141.4)
Fiber, g	22.7 (12.6)	20.5 (14.9)	20.7 (13.8)	16.6 (17.8)	23.7 (13)	21.8 (16.7)
Calcium, mg	482.7 (254.1)	461.5 (337)	558.8 (350.7)	472.9 (602.5)	531.3 (286.9)	487 (337.1)
Folate, µg	259.6 (214.5)	176 (271.8)	279 (239.4)	197.8 (280.1)	296.2 (243.3)	182.1 (339.3)
Iron, mg	14.1 (7.3)	13.1 (9.3)	14.1 (8.3)	12.1 (9.2)	16.1 (8.1)	15.4 (11.8)
Niacin, mg	16.6 (10.3)	13.7 (13.2)	17.8 (12.5)	15.7 (14.7)	19.5 (13.1)	15.8 (14.4)
Riboflavin, mg	0.6 (0.3)	0.6 (0.4)	0.7 (0.4)	0.6 (0.5)	0.8 (0.4)	0.7 (0.8)
Thiamine, mg	1 (0.6)	0.8 (0.8)	0.9 (0.6)	0.8 (0.8)	1.1 (0.7)	0.9 (0.9)
Vitamin A (RE), µg	879.2 (712.5)	649.7 (714.3)	1177.3 (937.5)	879.6 (1267.2)	944.5 (755.3)	690.1 (903.6)
Vitamin B6, mg	1.5 (0.8)	1.3 (0.9)	1.6 (0.9)	1.4 (1.3)	1.7 (0.8)	1.5 (1.1)
Vitamin B12, µg	2.4 (2)	1.8 (2.9)	2.7 (2.4)	2.1 (3.1)	2.5 (1.8)	2.1 (2.8)
Vitamin C, mg	69.7 (46.6)	55.7 (49.5)	73.4 (49.3)	60.6 (61.7)	73.7 (44.4)	70.1 (63.6)
Zinc, mg	6.3 (3.1)	5.8 (3.7)	6.7 (3.8)	6.3 (5.7)	7.5 (3.3)	7.2 (4.9)

24HR, 24hr recall; FRANI, Food Recognition Assistance and Nudging Insights; IQR, interquartile range; WR, weighed records.
[1] Number of person-days = 99, equal to number of subjects *(n* =36) multiplied by number of completed recalls.

probabilities of adequate micronutrient intake were low (<20%) for calcium, iron, zinc, riboflavin, and vitamin A. The MPA was estimated at 35%, 38%, and 41% for WR, FRANI, and 24HR methods, respectively (Table 3), with the differences relative to estimates of MPA prevalence from WR found to be statistically significant for FRANI (Δ = 3.5%, P = 0.001) and 24HR (Δ = 6.8%, $P < 0.001$), and for differences between FRANI and WR (Δ = 3.2%, P = 0.003).

On average, adolescents consumed ~6 food groups daily and more than 80% consumed at least 5 food groups per day. The proportion of days when adolescents consumed different food groups was similar among the 3 methods (Figure 1). WR demonstrated that almost all adolescents (92%–100%) consumed grains, meat, nuts and seeds, and other vitamin A-rich fruits and vegetables daily. Dairy and eggs were consumed by 40% and 38% of participants, respectively. However, fruits were only consumed by 25% of participants.

Bland–Altman plots with 95% of differences in intakes expressed as a ratio for log-transformed data for energy and nutrients as estimated by FRANI application compared with WR are displayed in Supplemental Figure S1. The difference in log-transformed nutrient intakes (FRANI or 24HR nutrient − observed nutrient) is equivalent to the ratio or proportion (FRANI or 24HR nutrient/observed nutrient).

Equivalence testing

When comparing ratios of log-transformed intakes from FRANI with WR (Figure 2A and Supplemental Table S1), we observed equivalence at the 10% bound for energy intakes (mean ratio = 1.00, 90% CI 0.91, 1.09); 15% bound for folate (1.01, 90% CI 0.89, 1.14); iron (0.94, 90% CI 0.86, 1.04); zinc (0.97, 90% CI 0.87, 1.08); niacin (0.98, 90% CI 0.87, 1.10); and vitamin B6 (1.03, 90% CI 0.93, 1.15). Protein, calcium, riboflavin, and thiamine intakes were found to be equivalent at the 20% bound. Similar comparisons between 24HR and WR found equivalence at the 15% bound for total carbohydrate intake (mean ratio = 1.03, 90% CI 0.95, 1.13) and 20% bounds for energy, fiber, calcium, thiamine, and vitamin A (Figure 2B and Supplemental Table S1). Wide bounds (>30%) were found for vitamin A (FRANI) and vitamin B12 (FRANI, 24HR), and

TABLE 3
Estimated probability of adequate intake among adolescent females in Accra, Ghana (n = 36) by WR, FRANI application, and 24HR methods

	EAR[1]	WR (n = 99)[2]	FRANI (n = 99)[2]	24HR (n = 99)[2]
Calcium, mg	960.0	0.0 (0)	2.9 (1.5)	0.3 (0.3)
Folate, µg	250.0	45.5 (4.5)	51.4 (4.9)	64.7 (10.7)
Iron, mg	7.0	13.1 (1.6)	9.9 (1.8)	18.9 (4.0)
Niacin, mg	1.3	85.7 (2.2)	87.3 (2.5)	91.2 (4.6)
Riboflavin, mg	0.8	0.1 (0.1)	0.3 (0.4)	0 .0(0.1)
Thiamine, mg	0.07	91 (2.4)	93.1 (1.9)	97.5 (1.7)
Vitamin A (RE), µg	490.0	0.1 (0.1)	8.4 (2.6)	0.5 (0.4)
Vitamin B12, µg	AI=4	55.2 (10.4)	62.9 (12.2)	59.2 (12.6)
Vitamin B6, mg	1.3	59.1 (5.6)	64.4 (10)	72.6 (12.1)
Vitamin C, mg	75.0	27.5 (6.7)	35.3 (11.5)	42 (18.6)
Zinc, mg	9.9	2.1 (0.9)	2.5 (1.1)	7.5 (4.4)
Mean probability of adequacy of micronutrients, %		34.5 (2.7)	38 (3.8)	41.3 (6.2)

24HR, 24hr recall; FRANI, Food Recognition Assistance and Nudging Insights; WR, weighed records;
[1] Estimated average requirement based on EFSA recommendations.
[2] Number of person-days=99, equal to number of subjects (=36) multiplied by number of completed recalls.

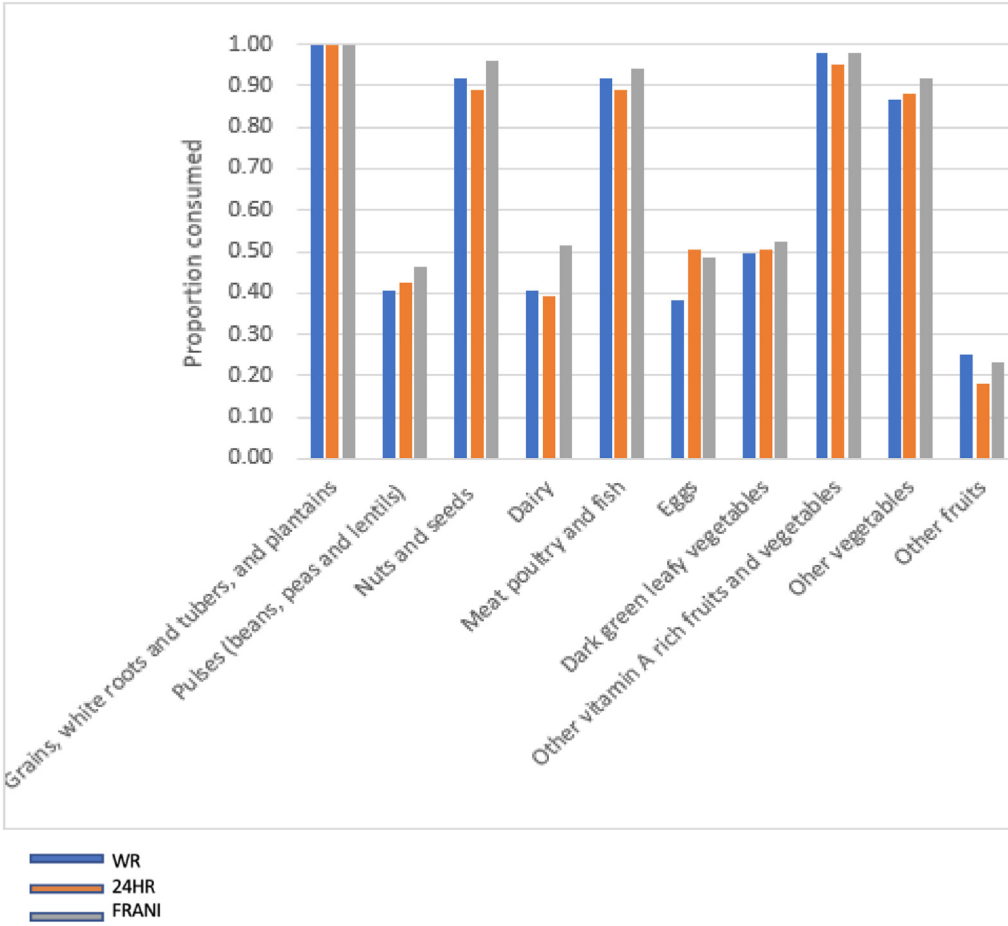

FIGURE 1. Food groups consumed by WR, FRANI application, and 24HR ($n = 36$). The mean number of food groups consumed was 6.63 for WR, 6.62 for FRANI, and 7.02 for 24HRs. FRANI, Food Recognition Assistance and Nudging Insights; WR, weighed records; 24HR, 24-hr recall.

riboflavin (24HR). The CCCs by nutrient between FRANI and WR ranged between 0.30 and 0.68, with similar CCCs found for 24HR and WR (ranging between 0.38 and 0.67) (Figure 3 and Supplemental Table S2).

Sources of error

Examination of the percentage of energy intake consumed by food group highlighted minor variations across FRANI and 24HR compared with WR (Table 4). However, more substantive variations were found in the quantities of food consumed by food groups. FRANI and 24HR methods appeared to underestimate most quantities consumed of all food groups except for “meat, poultry, and fish” and “eggs” food groups (and 24HR for “other vitamin A-rich fruits and vegetables”). Tests for statistically significant differences were not performed as the purpose of Table 4 is purely descriptive. Comparisons of food consumption episodes from FRANI and WR found levels of omission and intrusion errors of 31% and 16%, respectively. Omission and intrusion errors were lower when comparing 24HR with WR (21% and 13%, respectively). Further analysis of the most commonly consumed foods showed no clear bias in terms of over- or underreporting of consumption episodes or portion estimation for the different methods (Table 5).

Discussion

By comparing the estimates from FRANI with WR, the gold standard for dietary assessment, and with 24HR, a standard method commonly used for dietary assessment, this study provides new rigorous evidence on the relative validity of using innovative AI–assisted mobile phone technology to assess the diets of female adolescents in LMIC. The findings suggest that the AI–assisted dietary assessment can estimate energy intake in adolescent females within a 10% equivalence bound, whereas the energy intake estimate from 24HR was accurate at a 20% bound compared with WR. For FRANI, equivalence was within a 15% bound for folate, iron, zinc, niacin, and vitamin B6, and the intake of 5 more micronutrients estimated within a 20% bound. No estimates of micronutrient intake obtained from the 24HR method were accurate within a 15% equivalence bound, although intake of 3 micronutrients estimated through 24HR fell within a 20% bound. Errors in MPA prevalence by method were lower for FRANI (~10 and ~3 percentage points) than for 24HR (~20 and ~6 percentage points). Although these differences are relatively small in magnitude, they provide evidence that FRANI is at least as accurate, and may be marginally more accurate than human-assisted dietary assessment in this particular context.

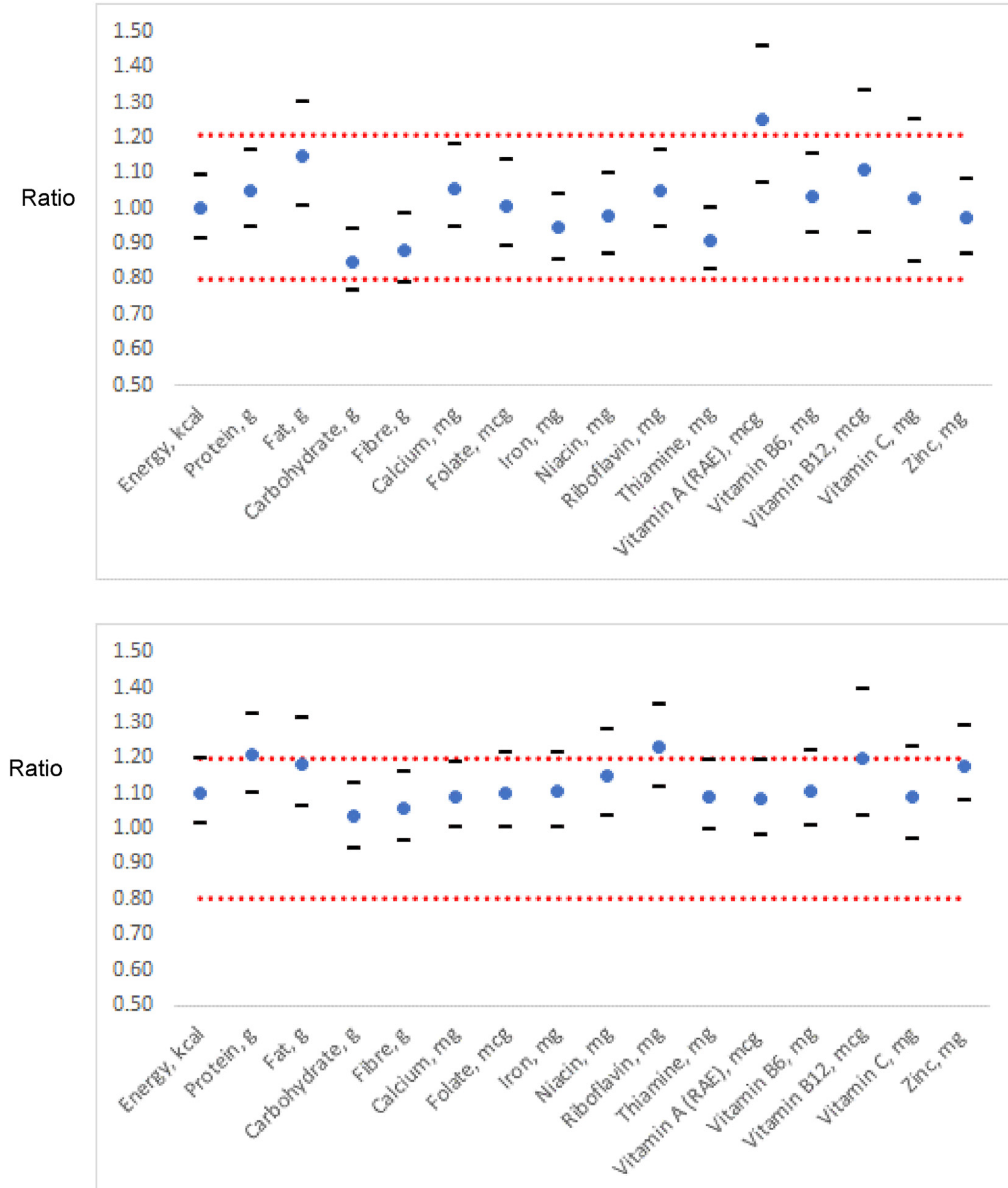

FIGURE 2. Equivalence testing of ratios of log-transformed nutrient intakes comparing (A) FRANI vs. WR and (B) 24HR vs. WR. FRANI, Food Recognition Assistance and Nudging Insights; WR, weighed records; 24HR, 24-hr recall.

These findings are consistent with a validation study of FRANI with a very similar design conducted in female adolescents in Thai Nguyen, a secondary city in Vietnam [24]. In that study, both FRANI and 24HR performed relatively more efficiently than in Ghana, with equivalence between FRANI and WR determined at the 10% bound for energy, protein, and fat and 4 nutrients (iron, riboflavin, vitamin B-6, and zinc), and at 15% and 20% bounds for carbohydrate, calcium, vitamin C, thiamin, niacin, and folate. Similar results were observed for differences between 24HRs and WR with a 20% equivalent bound for all nutrients except for vitamin A. The differences observed in the performance of FRANI could be explained by differences in the underlying food and recipe databases. It is also possible that the skills of enumerators performing the 24HR were different between the 2 countries. Further research is underway to examine the drivers of the underperformance of FRANI and 24HR in Ghana relative to Vietnam. One driver may be related to the socioeconomic differences in the 2 study populations. In Ghana, the study population was randomly selected across all income groups regardless of education status, whereas in Vietnam the study sample was selected from adolescent females attending high school.

We found wide bounds (>30%) for vitamin A (FRANI) and vitamin B12 (FRANI, 24HR), and riboflavin (24HR). These were likely due to a combination of estimation errors and large variance in the actual intake of these nutrients (partly due to the small sample size). For these 3 nutrients, the frequency of consumption of foods was low with extremely high nutrient content including gizzard, "sobolo," sardines, mackerel, herrings, and eggs, leading to extreme values skewing the relevant nutrient

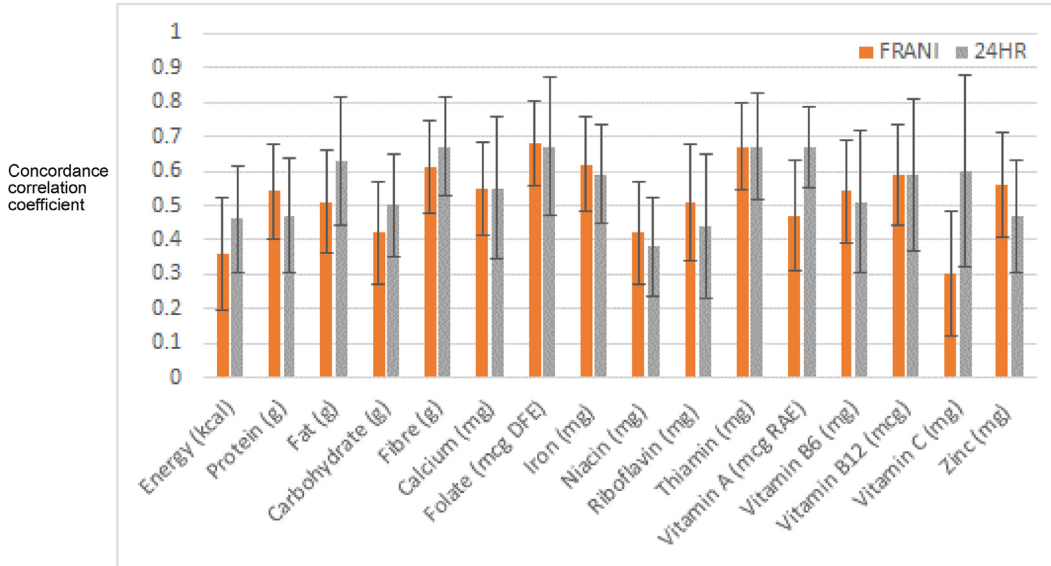

FIGURE 3. Concordance correlation coefficients of nutrient intakes on 3 d by WR, FRANI application, and 24HR (n = 36). The concordance correlation coefficient was estimated with adjustment for repeated measures. FRANI, Food Recognition Assistance and Nudging Insights; RAE, retinol activity equivalents; WR, weighed records; 24HR, 24-hr recall.

TABLE 4

Quantity of food consumed by major food group and share of energy intake from major food group over 3 d by WRs, FRANI application, and 24HR recall

Quantity consumed (g)	WR (n = 99)[1]		FRANI (n = 99)[1]		24HR (n = 99)[1]	
	Mean (SD)	Median	Mean (SD)	Median	Mean (SD)	Median
Grains, white roots and tubers, and plantains	624.1 (324.1)	552.0	465.0 (323.2)	381.6	619.2 (355.3)	606.6
Pulses (beans, peas, and lentils)	102.2 (145.9)	0.0	76.2 (123.5)	0.0	99.12(150.6)	0.0
Nuts and seeds	40.5 (96.1)	0.0	30.6 (84.4)	0.0	32.6 (87.3)	0.0
Dairy	75.0 (126.3)	0.0	30.8 (55.8)	0.0	69.1 (114.7)	9.0
Meat, poultry, and fish	279.7 (209.0)	286.0	279.1 (223.8)	222.0	301.1 (227.6)	272.0
Eggs	42.3 (80.0)	0.0	47.7 (72.7)	9.5	64.1 (91.3)	0.0
Dark green leafy vegetables	9.7 (28.0)	0.0	6.3 (25.6)	0.0	9.5 (28.2)	0.0
Other vitamin A-rich fruits and vegetables	369.1 (205.9)	361.0	337.4 (236.8)	293.0	372.0 (230.4)	370.8
Other vegetables	402.1 (259.1)	399.0	370.1 (284.5)	315.4	434.4 (276.2)	381.0
Other fruits	59.0 (120.5)	0.0	8.1 (23.0)	0.0	49.2 (109.2)	0.0
Share of energy intake	Mean (SD)	Median	Mean (SD)	Median	Mean (SD)	Median
Grains, white roots and tubers, and plantains	0.2 (0.1)	0.2	0.2 (0.16)	02	0.2 (0.1)	0.2
Pulses (beans, peas, and lentils)	0.0 (0.1)	0.0	0.0 (0.06)	0.0	0.0 (0.1)	0.0
Nuts and seeds	0.0 (0.0)	0.0	0.0 (0.05)	0.0	0.0 (0.0)	0.0
Dairy	0.1 (0.1)	0.0	0.0 (0.09)	0.0	0.1 (0.1)	0.0
Meat, poultry, and fish	0.1 (0.1)	0.1	0.1 (0.12)	0.1	0.1 (0.1)	0.1
Eggs	0.0 (0.1)	0.0	0.1 (0.08)	0.0	0.0 (0.1)	0.0
Dark green leafy vegetables	0.0 (0.0)	0.0	0.0 (0.0)	0.0	0.0 (0.1)	0.0
Other vitamin A-rich fruits and vegetables	0.2 (0.1)	0.2	0.3 (0.2)	0.2	0.2 (0.1)	0.2
Other vegetables	0.1 (0.1)	0.1	0.2 (0.1)	0.1	0.1 (0.1)	0.1
Other fruits	0.0 (0.1)	0.0	0.0 (0.0)	0.0	0.0 (0.1)	0.0

FRANI, Food Recognition Assistance and Nudging Insights; WR, Weighed Records

[1] Number of person-days = 99, equal to number of subjects multiplied by number of completed recalls.

intake distribution. Concerning the estimation errors for vitamin A intake in FRANI, lowering the standard portion size in the database on portion sizes for manual entry of "sobolo" (hibiscus drink) would likely increase the overall estimation accuracy and reduce the large variance observed.

To our knowledge, no other studies assess the validity of mobile technology for dietary assessment in adolescents in LMIC. A systematic review including 14 validation studies of mobile phone–based applications in high-income countries with 2 focusing on adolescents in Sweden [32] and Korea [33] examined the performance of mobile applications relative mostly to 24HR, with only 2 comparing with WR [34]. The analysis found that dietary record applications slightly underestimated food consumption compared with traditional dietary assessment methods (–85 kcal/d for energy; −19 g/d, −13 g/d, and −12 g/d for carbohydrate, fat, and protein intake, respectively). The evidence presented in this validation study is thus consistent with that reported in the emerging literature on this topic,

TABLE 5
Comparisons of reported consumption episodes and mean quantities eaten among most commonly consumed foods assessed using WR, FRANI, and 24HR

Food	Consumption episodes (*n*)			Mean quantity consumed (g)			Ratio of quantities consumed	
	WR	FRANI	24HR	WR	FRANI	24HR	FRANI/WR	24HR/WR
Shito	35	46	34	34	35	18	1.05	0.52
Banku	25	26	22	364	338	245	0.93	0.67
Tomato stew	25	24	23	52	35	52	0.67	0.99
Chicken fried	24	33	32	45	80	103	1.80	2.30
Rice jollof	24	25	25	286	249	271	0.87	0.95
Spaghetti	24	27	21	226	145	110	0.64	0.49
Egg boiled	23	27	22	48	71	60	1.46	1.24
Bread tea	22	31	15	97	126	324	1.31	3.36
Fish fried	20	16	19	59	57	67	0.97	1.13
Hausa Koko	17	22	16	353	204	454	0.58	1.28
Rice plain boiled	17	24	21	318	207	301	0.65	0.95
Waakye	17	20	16	299	168	345	0.56	1.15
Milk	15	1	33	33	44	31	1.35	0.95

FRANI, Food Recognition Assistance and Nudging Insights; WR, Weighed Records; 24HR, 24-hr recall.

highlighting the potential for new technologies to improve diet assessment methods and potentially reduce data collection costs.

A major strength of this analysis is the rigorous design of the validation study, including comparisons with both WR (as the gold standard for dietary assessment) and 24HR (the standard method commonly used in studies), and data collected by different enumerators across these 2 methods to reduce potential bias. The design included data collection on 3 nonconsecutive days, including week and weekend days, to provide a perspective on usual intake. Nutrient intakes were computed from a compilation of locally relevant food-composition databases and the West African Food-Composition Tables within which a majority of foods were identified. In the few cases where exact foods could not be found, nutrient values of similar foods were substituted.

Several limitations, however, are also apparent. First, the study was conducted in a relatively controlled environment, where FRANI use could be to some degree assisted by WR enumerators. This could lead to higher precision in FRANI estimation compared with that expected in real-world use. In parallel, the precision of the 24HR could potentially also be biased toward higher accuracy as participants were likely primed during the recall by FRANI use on the previous day, suggesting that the overall comparisons between FRANI and 24HR presented here may also hold in a real-world setting. When 24HRs do not account for all foods and beverages consumed, this would lead to less precision on the nutrient intakes and wider confidence bounds. This topic remains an important area of ongoing research. In addition, although the sample size was small, it was in line with expectations for a pilot study, and participants were recruited randomly from a population representative of adolescents in Accra, thus increasing the external validity of these results. In addition, due to challenges in matching records across the 3 methods, the analytical sample included 98 out of the 108 records resulting in wider CIs. However, the degree of acceptable error is open for debate and should be carefully considered in the context of the dietary information required. In this study, although the 15% bound for energy is equal to approximately 280 kcals, which is similar or better than some validation studies in adults in the literature, this level of precision may be considered unacceptable when high degrees of accuracy are required. Finally, although the expectation for the WR was to cover the full 24-h period, for logistic reasons enumerators were personally only covering the period from early morning (~6 am) to late evening (after last meal was supposedly consumed). In this analysis, we matched consumption times across the 3 methods, excluding food consumption reported outside the WR period.

In conclusion, we found that FRANI AI–assisted dietary assessment could accurately estimate nutrient intakes in adolescent females compared with WR in urban Ghana. FRANI estimates were at least as accurate as those provided through 24HR. Further improvements in food recognition and portion estimation in FRANI could reduce errors and improve overall nutrient intake estimations. Further research is ongoing, including pilots on the feasibility of using FRANI to nudge adolescents toward healthy food choices in LMICs. Although the potential for new technologies such as FRANI to have an impact at scale is clear, real-world evaluations are needed to ensure that the technology is feasible, valid, and effective.

Author contributions

A.G., G.F., and P.N. designed the research; P.M., R.G., F.D., and D.H. developed the FRANI application; P.H.N., L.M.T., N.T.H., B.K., P.M., R.G., G.F., B.B., A.A., B.C.B., J.A., A.K., F.D., D.H., and A.G. conducted the research; A.G. and G.F. analyzed and interpreted the data; G.F., A.G., and P.N. wrote the paper; G.F., P.H.N., A.G., J.A., B.K., and P.M. provided the critical revision of the manuscript for important intellectual content. All authors have read and approved the final manuscript.

Data Availability

Data described in the manuscript, code book, and analytic code will be made available upon request.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.tjnut.2023.06.001.

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