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Evaluation of PIQNIQ, a Novel Mobile Application for Capturing Dietary Intake

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ABSTRACT

Background: Accurate measurement of dietary intake is vital for providing nutrition interventions and understanding the complex role of diet in health. Traditional dietary assessment methods are very resource intensive and burdensome to participants. Technology may help mitigate these limitations and improve dietary data capture.

Objective: Our objective was to evaluate the accuracy of a novel mobile application (PIQNIQ) in capturing dietary intake by self-report. Our secondary objective was to assess whether food capture using PIQNIQ was comparable with an interviewer-assisted 24-h recall (24HR).

Methods: This study was a single-center randomized clinical trial enrolling 132 adults aged 18 to 65 y from the general population. Under a provided-food protocol with 3 menus designed to include a variety of foods, participants were randomly assigned to 1 of 3 food capture methods: simultaneous entry using PIQNIQ, photo-assisted recall using PIQNIQ, and 24HR. Primary outcomes were energy and nutrient content (calories, total fat, carbohydrates, protein, added sugars, calcium, dietary fiber, folate, iron, magnesium, potassium, saturated fat, sodium, and vitamins A, C, D, and E) captured by the 3 methods.

Results: The majority of nutrients reported were within 30% of consumed intake in all 3 food capture methods ($n = 129$ completers). Reported intake was highly (>30%) overestimated for added sugars in both PIQNIQ groups and underestimated for calcium in the photo-assisted recall group only ($P < 0.001$ for all). However, in general, both PIQNIQ methods had similar levels of accuracy and were comparable to the 24HR except in their overestimation (>30%) of added sugars and total fat ($P < 0.001$ for both).

Conclusions: Our results suggest that intuitive, technology-based methods of dietary data capture are well suited to modern users and, with proper execution, can provide data that are comparable to data obtained with traditional methods. This trial was registered at clinicaltrials.gov as NCT03578458. *J Nutr* 2021;151:1347–1356.

Keywords: dietary intake assessment, mobile applications, nutrients, adult, humans, self-report

Introduction

The collection of accurate and comprehensive dietary data facilitates the provision of effective nutrition interventions and, more broadly, deepens our understanding of the complex relationship between diet and health. However, traditional dietary assessment methods that capture granular data are not only burdensome for respondents and investigators but also ill-suited to modern users. The adoption of technology, particularly through smartphone ownership and internet usage, continues to grow worldwide (1), and research participants have expressed preference for digital tools over traditional "pen-and-paper" methods for logging dietary intake (2–6). In addition, the use of smartphone apps for health and fitness, which includes apps with diet-tracking features, grew by >30% from 2014 to 2017 (7). While popular, these and other technology-based diet-tracking tools require further development for validity (8, 9) and ease of use (10).

Dietary assessment tools that rely solely on self-report are natural targets for improvement. These include pen-and-paper dietary records and the interviewer-administered 24-h dietary recall (24HR), both of which have been adapted for technology platforms [as diet-tracking apps and the automated self-administered 24-h recall (ASA24) (11), respectively]. Self-report, though a standard feature of dietary assessment tools, is limited by data quality issues such as human memory, social desirability bias, and altered energy intake on reporting days, e.g., to simplify the recording process and reduce the associated burden (12–14). Self-reported dietary assessments are also limited by the reporter's ability to estimate portion

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size (9, 15–17), a limitation often addressed by the inclusion of reference photos or other features in web-based research tools [e.g., the ASA24 (11)] but not apps. By incorporating accurate and intuitive features, apps and other diet-tracking tools have the potential to minimize these limitations and improve data quality. For apps, supplements or alternatives to manual entry are key; these include features that serve as memory aids or facilitate recall [e.g., push notifications or text message reminders (18–20) and image capture for taking photos of food items (21)] as well as automated or semi-automated data entry features [e.g., barcode scanners (2, 22–24), autocompletion of text input, predictive text search options (25), and prompts for commonly forgotten or "linked with" food items (15, 26)]. More broadly, technology tools that administer dietary recalls can be enhanced by multiple passes (27), food probes (28), and visual cues [e.g., food photographs (29) and other features for portion size estimation].

The newly developed PIQNIQ app aims to mitigate issues associated with self-report by incorporating common data entry features, such as text entry and dropdown menus to facilitate choice, as well as a portion size selector—a timesaving feature with a slider for visually estimating food or drink portions. In this report, we describe a study evaluating the accuracy of PIQNIQ in capturing self-reported dietary intake across 3 healthy dietary patterns. Our primary objective was to assess the accuracy of 2 food capture methods using PIQNIQ, comparing the energy and nutrient content of reported foods with those of foods actually consumed. Our secondary objective was to assess whether these PIQNIQ-based methods are comparable with 24HR. To compare reported and consumed dietary intakes, a provided-food protocol was used.

Methods

The research protocol was reviewed and approved by the Tufts Health Sciences Institutional Review Board. All study measurements were conducted by trained nurses and research staff at the Jean Mayer USDA Human Nutrition Research Center on Aging (HNRCA) at Tufts University in Boston, Massachusetts. The study is registered at https://clinicaltrials.gov/ct2/show/NCT03578458. Further, in this report, we adhere to best practice guidelines for reporting on new technologies for dietary assessment (30).

Study design

This study was a single-center, nonblinded, randomized clinical trial using equal allocation to each food capture method, i.e., the way in which participants recorded dietary intake. The food capture methods tested were 2 PIQNIQ-based methods and 24HR.

To achieve the primary objective, the energy and nutrient content of foods self-reported by the participants using PIQNIQ were compared with the energy and nutrient content of the foods actually consumed by the participants (provided food minus uneaten, returned food). To achieve the secondary objective, interviewer-administered 24HRs using multiple-pass methodology (31–33) were used to collect dietary intake data; the accuracy of self-reported data from PIQNIQ food capture methods and 24HR were then compared.

Participants

Recruitment and informed consent.

From May to September 2018, participants were recruited from the general public using flyers, bulletin boards, websites, and direct mailings (only for volunteers in the HNRCA database who had previously agreed to be contacted for future studies). Participants were enrolled on a rolling basis until target numbers were met (n = 132; 44/group; **Supplemental Figure 1**). Written informed consent was obtained from all study participants prior to primary data collection.

Eligibility.

Initial eligibility was determined via phone by a prescreening questionnaire administered after obtaining verbal consent. Inclusion and exclusion criteria were confirmed at an in-person screening, and participants who remained interested and eligible were enrolled into the study. Inclusion criteria included generally healthy men and women who were 18 to 65 y of age, ate a wide variety of foods from all food groups; had a BMI (in kg/m^2) $\geq$18 and <30, were able to read and write in English, had a mobile phone with a compatible operating system (iOS 11 or higher; Android 6 or higher), were willing to download the app, and were willing and able to sign written informed consent. Exclusion criteria included presence of active disease that would prevent normal dietary intake and/or result in weight loss (e.g., irritable bowel syndrome, Crohn disease, celiac disease), medical complications or chronic illness that would prevent full participation (e.g., active cancer), pregnant or lactating women, a diagnosed eating disorder, a diagnosed mental health condition that had not been stable within the previous 6 months, mobility limitations, special dietary requirements or severe allergies that prevented the consumption of major food groups, vegetarianism, planning to partake in vigorous physical training/exercise during the study period (e.g., training for or running a marathon), overnight shift work, current or previous experience with dietary data collection or analysis, and concurrent participation in another research study at any point during the study period.

Random assignment

Upon enrollment, participants were randomly assigned to 1 of 3 food capture methods and then a study menu sequence; each participant's food capture method remained consistent across menus. Random assignment was implemented through the random assignment module in REDCap, using a sequence with block random assignment of size 4 (generated using the random module in Python). A bioinformatics specialist independent of the study built and managed the random assignment schema.

Study visits and activities

Following random assignment, participants completed study orientation, including the scheduling of study visits and a review of study-specific requirements and their assigned food capture method. For app-based methods, participants completed a brief training session using a study-provided smartphone and plastic models of food items that did not correspond to items on the study menus. For 24HR, participants met with a trained member of the HNRCA dietary assessment unit (DAU) to review 24HR instructions and the accompanying Food Amounts Booklet. Study-provided smartphones were used for training sessions only, and participants downloaded the PIQNIQ app on their personal phones for the duration of the study. Study procedures were completed both on and off site. The first day of the first menu occurred ≤7 d after enrollment.

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Supplemental Table 1–3 and Supplemental Figure 1 are are available from the "Supplementary data" link in the online posting of the article and from the same link in the online table of contents at https://academic.oup.com/jn.

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Abbreviations used: DAU, dietary assessment unit; FNDDS, USDA Food and Nutrient Database for Dietary Studies; HNRCA, Jean Mayer USDA Human Nutrition Research Center on Aging; NDSR, Nutrition Data System for Research; 24HR, 24-h dietary recall.

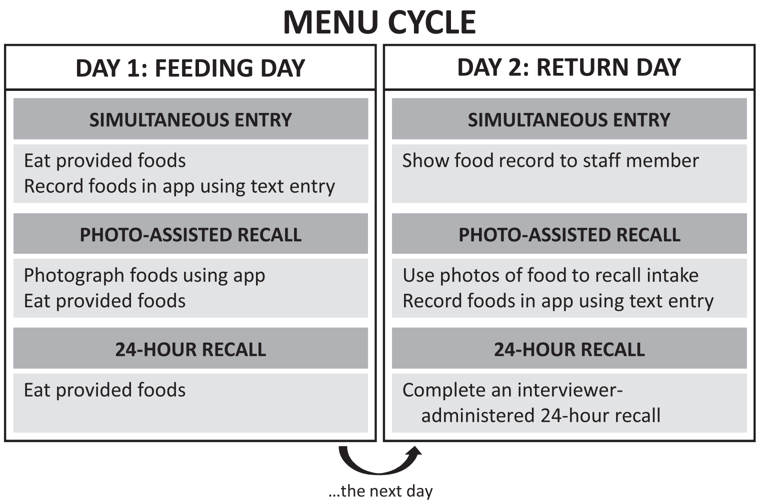

FIGURE 1 Study visits for each menu cycle based on assigned food capture method. Day 1 procedures were completed on site for breakfast and off site for all other eating occasions; Day 2 procedures were completed on site only. This cycle was completed for each of the 3 menus; the participant's food capture method remained consistent across menus, and menus could not be completed on consecutive days.

Participants partook in three 2-d menu cycles (Figure 1), receiving 1 menu plan per cycle. Participants were required to visit the HNRCA on both days of each cycle. On the first day of each cycle (the "feeding day"), the participant consumed a study-provided breakfast on site and received preportioned meals and snacks for off-site consumption throughout the day. On the second day (the "return day"), the participant returned to the HNRCA with study containers and any uneaten food for weight measurement by study staff. Based on their assigned group, participants completed their food capture method on 1 or both days of each menu cycle (Figure 1). Menu cycles were separated by ≥1 day (median: 7 d), and the app was locked on days between visits to reduce learning effect and ensure that all collected data were exclusive to study days. The study duration for each subject was approximately 21 d.

Study groups

Group 1: simultaneous entry with PIQNIQ app.

Participants assigned to the simultaneous entry group used the app to log food intake. On each feeding day, participants were instructed to use text entry to log their intake of study-provided foods simultaneous with or immediately after every eating occasion. When estimating portion size, participants could use the visual portion size selector (default option) or text entry.

Group 2: photo-assisted recall with PIQNIQ app.

Participants assigned to the photo-assisted recall group also used the app to log food intake. On each feeding day, participants were instructed to use the in-app photography feature to capture photos of study-provided foods during every eating occasion; participants did not have access to food-logging features at this time. Instead, the following day at the HNRCA, participants used these photos to prompt recall and then record intake of study-provided foods in the app; this recall was not assisted by study staff. To log food items, participants used text entry and, if desired, the default portion size selector. This method was designed to simulate a record-assisted (34, 35) or image-assisted (36, 37) 24HR and to test whether capturing photos of consumed foods would enhance recall capabilities.

Group 3: 24-h recall.

On each feeding day, participants assigned to the 24HR group consumed the provided food but did not record its consumption. When participants returned on the subsequent day, they met with a trained member of the HNRCA DAU to complete an interviewer-administered 24HR. A Food Amounts Booklet and measuring cups and spoons were available as needed to assist in estimating portions. Recalls were completed using the multiple-pass method and DAU staff were blinded to the menus and food items received by participants (31–33). Dietary intake data were collected and analyzed using Nutrition Data System for Research (NDSR) software version 2017, developed by the Nutrition Coordinating Center (38, 39).

Provided foods

Three 1-day menu plans were provided to participants: healthy US, vegetarian, and Mediterranean. This was done so that the participants would be exposed to a wide variety of foods, some of which might have been outside their normal daily diet. Menu sequence was randomly assigned within each of the 3 study groups. Each plan adhered to a healthy eating pattern described in the 2015–2020 USDA Dietary Guidelines (healthy US-style eating pattern, healthy vegetarian eating pattern, and healthy Mediterranean-style eating pattern). Each menu included 3 meals and snacks. Unsweetened noncaloric beverages such as water, black tea, and black coffee were provided for breakfast and allowed ad libitum throughout the day; however, sweetened beverages, even if noncaloric, were not permitted.

Provided menus.

Menu plans were developed by an HNRCA-registered dietitian, and all provided foods were prepared on site by dietary services staff. NDSR software version 2017 was used to calculate nutrient values for all provided foods, and templates with incremental calorie levels were created for each menu plan. Upon enrollment, the estimated energy requirement of each participant was calculated using dietary reference intake equations with the "low active" physical activity coefficient (40). To ensure energy requirements were met, this value was rounded up to the calorie level of the nearest menu template.

Consumed food and adherence.

Participants were instructed to consume all of the provided foods and no off-menu items during the feeding day of each cycle. If for whatever reason participants consumed off-menu items, they were instructed to exclude these items from self-report. These adherence guidelines were developed because data on the consumption and report of off-menu items were not relevant to achieving the study objectives.

In addition, participants were instructed to complete meal checklists to track the receipt and consumption of food items during each menu cycle. If desired, these checklists also could be used to record any off-menu items or approved beverages that were consumed during a feeding day. So as to not bias food choice or portion size estimation, checklists

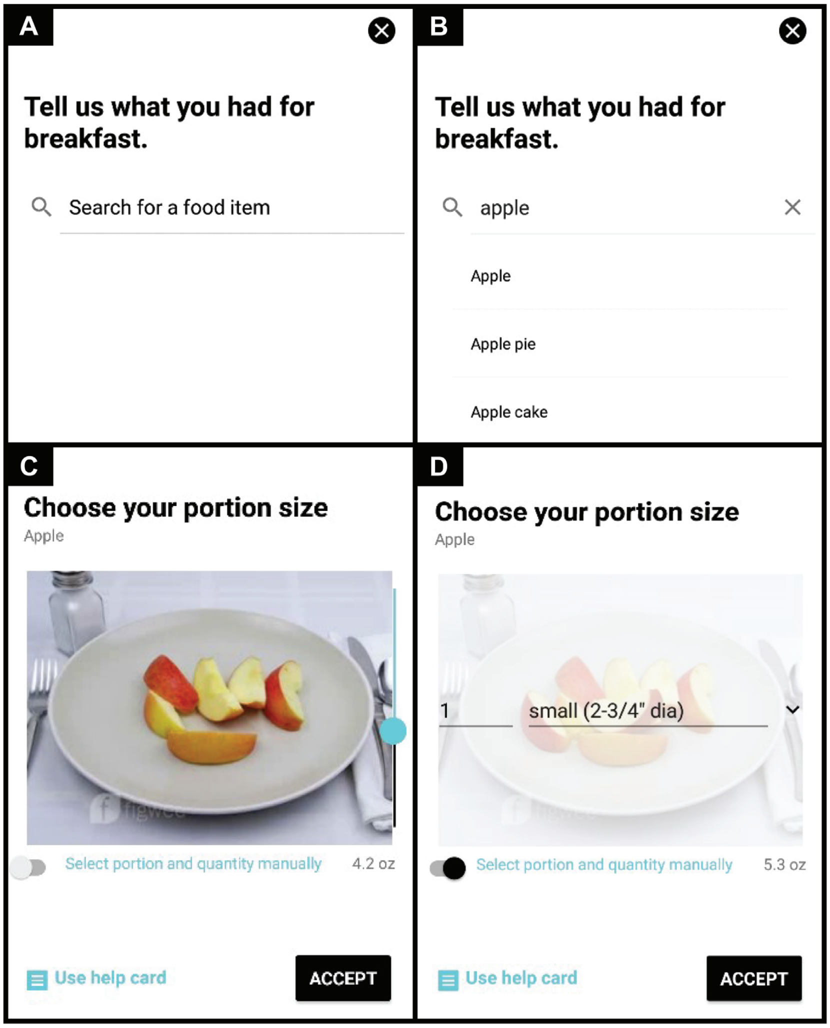

FIGURE 2 Logging an apple in PIQNIQ. (A) By choosing to add a food item for breakfast on PIQNIQ's diary screen (not shown), the user initiates a text search. (B) The user types the desired food item ("apple"), which automatically populates a list of related items ("apple," "apple pie," "apple cake"). (C) By choosing "apple," the user is brought to the portion size selection screen, with the visual portion size selector as the default option. The slider to the right of the image can be moved up or down to increase or decrease portion size, and the amount of apple on the plate will change accordingly. By tilting the phone backward and forward, the user can change his viewing angle of the food item and place setting. (D) If the user does not wish to use the portion size selector, he can toggle to manual entry by tapping the switch labeled "Select portion and quantity manually." In this example, the user selects his desired unit (small; $2\frac{3}{4}''$ in diameter) from a dropdown menu and enters the item's value ("1") using text entry. The available units vary by food item.

only included very generic descriptions of the provided foods (e.g., "main course," "side dish," "beverage") and did not indicate portion sizes or actual food descriptions.

Mobile phone application

The PIQNIQ app was developed by Nestlé Research (Société des Produits Nestlé SA) using C#/Xamarin, a language platform that combines the advantages of a single shared codebase for maintainability and consistency with the performance optimizations and familiar user experience available for native-device compilation (in this case, iOS and Android). PIQNIQ exchanged JavaScript Object Notation–encoded messages with a Python backend, which was hosted on the Amazon web service using representational state transfer application programming interface calls over encrypted hypertext transfer protocol. The app was provided to study participants as a closed beta version from both Google Play and the Apple App Store for the duration of the study only, and both installation and uninstallation of the app were completed by study staff. After the participant completed or withdrew from the study, the Nestlé developer team deactivated the user account.

After the first installation and login on a new device, PIQNIQ downloaded a food image database of weighted and graduated portions [Figwee (41), licensed from Bellwether Ideas, LLC], which was used by the app's portion size selector. In logging a food item, the user typed a search query (e.g., apple) and PIQNIQ sent the query to the backend server, which returned the best matches from a freeform search index built around the USDA Food and Nutrient Database for Dietary Studies (FNDDS, version 2011–2012) and a minimal number of food items (mostly spices) from the National Nutrient Database for Standard Reference food composition databases (version 28). Once a food item was selected, the user could estimate its portion size with the visual portion size selector (default option) or by toggling to manual entry (text entry for the item's value; dropdown menu for the item's unit). Each item was presented on/in appropriate dishware to aid the user in selecting portion size. Once the portion size was selected, the app logged the food item, portion size (in grams), and nutritional information from the reference food code database to the backend database. Screenshots of PIQNIQ are shown in Figure 2. In this example, the user logs an apple for breakfast (both portion size selection options are shown for reference).

Outcome measurements

Our primary objective was to assess the accuracy of food capture methods using PIQNIQ (simultaneous entry and photo-assisted recall), and our secondary objective was to assess whether food capture using PIQNIQ is comparable with that using a traditional interviewer-assisted 24HR. A provided-foods protocol was used to compare reported with consumed dietary intake of energy and the following nutrients: total fat, carbohydrates, protein, added sugars, calcium, dietary fiber, folate, iron, magnesium, potassium, saturated fat, sodium, and vitamins (A, C, D, and E).

Energy and nutrient intakes were obtained for each food capture method during the 3 menu cycles. At baseline, a demographic questionnaire was completed, and at study close, an end-of-study survey was completed for study-specific feedback. Participants randomized to a PIQNIQ group also completed an app-specific feedback survey. In general, responses were rated on a 5-point Likert or Likert-type scale, but open-ended responses were requested as well; feedback was collected on app use, preferences, and suggestions for improvement.

Statistical analyses

A participant's mean intake was calculated by taking geometric means over all completed menus for each nutrient component. The statistical software R v3.6 (R Core Team 2019) was used for all analyses.

Accuracy was measured by calculating mean bias for each nutrient within each method. Average reported and consumed intakes from each participant were natural log transformed, and differences between the reported and consumed intake, which represented bias in reporting, were calculated for each participant. No patterns were detected to indicate nonnormality in distribution for any of the nutrient components (not shown). The differences are expressed as a ratio (percentage accuracy relative to consumed), and this mean bias is presented in tables in ratio form. Ninety-five percent CIs for mean bias and P values are reported based on paired t-tests of the log differences between reported and consumed intake.

Relative mean bias was compared across the 3 methods using ANOVA on natural log–transformed differences between reported and consumed amounts, with Tukey Honest Significant Difference post-hoc tests for pairwise comparisons. Residuals from ANOVA were examined graphically to confirm adherence to normality and equal variance model assumptions. Boxplots by method (not shown) were used to assess any change in mean bias across the 3 menu cycles and rule out any indication of period effects (potential learning curve in the food capture method). To account for the multiple testing for energy and 16 nutrients, a Bonferroni-corrected α of 0.05/17 was considered for statistical significance (i.e., P values < 0.003 were considered significant). The Bonferroni-corrected P values are noted in the Results section as the adj P value, and the tables reflect the unadjusted P values with a footnote indicating the use of the Bonferroni-corrected α. P values that remain significant after adjustment are indicated in the tables.

Sensitivity analyses were conducted after excluding 4 participants who reported extremely high or low mean total energy intake ($> \pm 2$ SD from the mean; reported mean $>$4000 kcal/d or $<$850 kcal/d) and were identified as outliers. All 4 outliers had been assigned to an app-based food capture method.

Nutrient values for consumed foods were calculated from food codes in the NDSR database. However, reported nutrients from app-sourced data were derived from FNDDS food codes that were linked through the app. To reconcile nutrient differences between the NDSR and FNDDS databases, an adjustment was applied to energy and nutrients derived from FNDDS. Nutrient composition for each of the 3 provided menus was entered into the 2 databases by a registered dietitian, and relative change was calculated by the following formula: $\text{value}_{\text{NDSR}}/\text{value}_{\text{FNDDS}}$. Each subject's reported nutrients from FNDDS for each menu were multiplied by the relative change using the adjustment factor. This adjustment operates the same way as a statistical covariate and facilitates interpretation as an adjustment for database differences. Values derived from NDSR remain unchanged, including all consumed nutrient values and both consumed and reported values from participants in the 24HR group.

Results

Descriptive results for participants in each of the 3 groups (24HR compared with app groups)

As shown in **Table 1**, the majority of participants in the study sample were female, with a mean age of 35 ± 16 y, normal-weight BMI, and estimated total daily energy expenditure of 2300 kcal. Participants were highly educated, predominantly white, and not Hispanic or Latino (Table 1). Random assignment produced groups that were comparable at baseline with no significant differences in participant characteristics. Dropout rate was very low, with only 3 of 132 enrolled participants (2.3%) not completing all study menus (**Supplemental Figure 1**).

There were 125 participants who were included in the sensitivity analysis. Comparison of participant characteristics across the 3 groups were consistent with the full sample of 132.

Results from the app-specific feedback survey showed that only 32% of participants had previously used a diet-tracking app. Further, 86% of participants agreed that "PIQNIQ was easy to use," and 98% indicated that they used the visual portion size selector for estimating portion size. Eighty-nine percent of participants agreed and 0% disagreed that "overall, PIQNIQ provided helpful tools for estimating portion sizes" (data not shown).

Mean accuracies of reported compared with consumed intake by food capture method (mean bias)

Compared with consumed total energy intake, self-reported total energy intake was, on average, 14% higher (adj $P = 0.03$) in the simultaneous entry group, 9% higher (adj $P = 0.87$) in the photo-assisted recall group, and 1% lower (adj $P > 0.99$) in the 24HR group (**Table 2**).

For the simultaneous entry group (Table 2), added sugars had the largest estimated mean bias, with reported intake 72% higher than consumed intake (adj $P < 0.001$). Other nutrients for which the reported intakes were overestimated included carbohydrates (18%; adj $P = 0.02$), total fat (21%; adj $P < 0.001$), and vitamin A (18%; adj $P < 0.001$). Mean reported intakes of calcium and vitamin E were 26% and 24% lower than consumed intakes, respectively (adj $P < 0.001$ for both). No statistically significant bias (adj $P > 0.05$) was observed for fiber, saturated fat, protein, vitamin C, vitamin D, folate, iron, magnesium, sodium, or potassium.

For the photo-assisted recall group, only 3 nutrients had a mean estimated bias that was significantly different from zero ($P < 0.001$ for all; Table 2). Added sugars had the largest estimated mean bias, with reported 61% higher than consumed intakes (adj $P < 0.001$). In addition, reported estimates were 18% higher than consumed intakes for sodium and 33% lower than consumed for calcium (adj $P < 0.001$ for both). No significant bias (adj $P > 0.05$) was estimated for carbohydrates; fiber; total fat; saturated fat; protein; vitamins A, C, D, or E; folate; iron; magnesium; or potassium.

For the 24HR group, 5 nutrients had a significant estimated mean bias (adj $P < 0.05$; Table 2). Compared with consumed intake, mean reported intake was overestimated by 27% for sodium, 18% for magnesium (adj $P < 0.001$ for both), and 12% for potassium (adj $P = 0.02$). Mean reported intakes for calcium and total fat were 25% (adj $P < 0.001$) and 13% (adj $P = 0.02$) lower than consumed intakes, respectively. No significant bias (adj $P > 0.05$) was estimated for carbohydrates; added sugars; fiber; saturated fat; protein; vitamins A, C, D or E; folate; or iron.

TABLE 1 Baseline subject characteristics by food capture method[1,2]

	Simultaneous entry ($n = 43$)	Photo-assisted recall ($n = 43$)	24-h recall ($n = 43$)	*P* value[3]
Gender, *n* [%]				0.27
Male	12 [28]	9 [21]	16 [37]	
Female	31 [72]	34 [79]	27 [63]	
Age, y	36 (16)	35 (15)	35 (15)	0.89
Body weight, kg	67 (12)	67 (13)	67 (13)	0.98
BMI, kg/m^2	24 (3)	24 (3)	23 (3)	0.61
BMI category, kg/m^2				0.70
<25, *n* [%]	29 [67]	28 [65]	32 [74]	
≥25, *n* [%]	14 [33]	15 [35]	11 [26]	
TDEE, kcal/d	2306 (336)	2283 (314)	2363 (379)	0.54
Education, *n* [%]				0.11
≤11th grade	1 [2]	2 [5]	0 [0]	
12th grade or GED	6 [14]	3 [7]	2 [5]	
Some college or associate degree	10 [23]	7 [16]	11 [26]	
College	19 [44]	20 [47]	12 [28]	
Nondoctoral graduate degree	4 [9]	10 [23]	14 [33]	
Doctoral degree	3 [7]	1 [2]	4 [9]	
Race, *n* [%]				0.56
American Indian or Alaska Native	0 [0]	2 [5]	0 [0]	
Asian	9 [21]	8 [19]	8 [19]	
Native Hawaiian or other Pacific Islander	0 [0]	0 [0]	1 [2]	
Black or African American	8 [19]	9 [21]	4 [9]	
White	24 [56]	21 [49]	29 [67]	
>1 race	2 [5]	2 [5]	1 [2]	
Unknown	0 [0]	1 [2]	0 [0]	
Ethnicity, *n* [%]				0.73
Hispanic or Latino	3 [7]	6 [14]	3 [7]	
Not Hispanic or Latino	39 [91]	37 [86]	39 [91]	
Unknown	1 [2]	0 [0]	1 [2]	

[1]Data are expressed as means ± SDs, or frequency [%]. GED, general education development; TDEE, estimated total daily energy expenditure.
[2]Simultaneous entry and photo-assisted recall are app-based food capture methods.
[3]*P* values shown are from 1-way ANOVA or Fisher exact test.

In the sensitivity analysis (**Supplemental Table 1**), from which 4 extreme over- and underreporters in the app groups were excluded, mean reported intake in the simultaneous entry group was overestimated for 6 additional nutrients: saturated fat (adj $P < 0.001$), vitamin C (adj $P = 0.03$), folate (adj $P = 0.03$), magnesium (adj $P < 0.001$), sodium (adj $P < 0.001$), and potassium (adj $P = 0.03$). However, the estimates of mean bias changed no >2% in comparison to the main analysis , with the exception of added sugars, which changed by 5% (72% and 77% higher mean reported intake in the main and sensitivity analyses, respectively). For the photo-assisted recall group, only 1 additional nutrient had a significantly different mean bias: carbohydrates, which were overestimated by an additional 3% (adj $P = 0.02$).

Comparison between accuracies of reported and consumed intake by method (relative mean bias)

Relative mean bias was not significant between the 2 app groups (our primary objective) for energy or any of the 16 nutrients studied (adj $P > 0.99$ for all). Compared with 24HR (our secondary objective), both app methods provided similar estimates for energy and most nutrients except added sugars and total fat, both of which were overestimated (adj $P < 0.001$ for both; Table 3).

In the sensitivity analyses, relative mean bias remained nonsignificant between the 2 app groups for energy and all nutrients (adj $P > 0.99$ for all; **Supplemental Table 2**). Findings for comparisons of the app groups with the 24HR remained similar to the findings in the total sample except for 2 additional nutrients that were significantly overreported in the simultaneous entry group (total energy: adj $P = 0.03$; vitamin C: adj $P = 0.046$).

Accuracies of reported compared with consumed intake between participants with normal-weight and overweight BMI

Relative mean bias between participants with normal weight (<25) and overweight (≥25) BMI for the difference between self-reported and consumed foods is shown in **Supplemental Table 3**. No significant estimated relative bias was observed between these groups for any of the food capture methods (adj $P > 0.05$ for all comparisons after Bonferroni adjustment).

Discussion

Our findings indicate that compared with recording measurements of actual dietary intake, self-reported participant intake using simultaneous entry (i.e., logging intake of study-provided foods simultaneously with or immediately after every eating occasion) resulted in overestimation of intakes of energy, carbohydrates, added sugars, total fat, and vitamin A and

TABLE 2 Estimated mean bias between reported and consumed foods by food capture method in completers[1,2]

	Simultaneous entry ($n = 43$)		Photo-assisted recall ($n = 43$)		24-h recall ($n = 43$)	
	Mean bias (95% CI)	*P* value	Mean bias (95% CI)	*P* value	Mean bias (95% CI)	*P* value
Energy, kcal/d	1.14 (1.05, 1.24)	0.002[3]	1.09 (1.00, 1.19)	0.05	0.99 (0.93, 1.05)	0.71
Carbohydrates, g/d	1.18 (1.07, 1.29)	0.001[3]	1.10 (1.00, 1.22)	0.04	1.04 (0.97, 1.10)	0.25
Added sugars, g/d	1.72 (1.44, 2.05)	<0.001[3]	1.61 (1.35, 1.92)	<0.001[3]	0.87 (0.78, 0.98)	0.02
Fiber, g/d	1.06 (0.95, 1.18)	0.27	0.98 (0.88, 1.08)	0.64	1.04 (0.97, 1.11)	0.26
Total fat, g/d	1.21 (1.10, 1.33)	<0.001[3]	1.15 (1.03, 1.28)	0.02	0.87 (0.80, 0.94)	0.001[3]
Saturated fat, g/d	1.16 (1.06, 1.28)	0.003	1.12 (1.00, 1.25)	0.04	1.04 (0.96, 1.13)	0.34
Protein, g/d	0.96 (0.89, 1.04)	0.28	0.95 (0.87, 1.03)	0.19	1.04 (0.97, 1.11)	0.26
Vitamin A, μg/d	1.18 (1.08, 1.29)	<0.001[3]	1.07 (0.95, 1.20)	0.25	1.02 (0.94, 1.11)	0.63
Vitamin C, mg/d	1.14 (1.04, 1.26)	0.01	1.12 (0.98, 1.27)	0.09	0.93 (0.85, 1.01)	0.10
Vitamin D, μg/d	1.01 (0.94, 1.09)	0.79	1.05 (0.90, 1.22)	0.52	1.08 (0.96, 1.22)	0.18
Vitamin E, mg/d	0.76 (0.66, 0.86)	<0.001[3]	0.83 (0.72, 0.97)	0.02	0.95 (0.84, 1.08)	0.41
Folate, μg/d	1.16 (1.05, 1.29)	0.01	1.06 (0.95, 1.17)	0.29	1.10 (1.02, 1.19)	0.01
Iron, mg/d	1.00 (0.92, 1.10)	0.91	1.01 (0.89, 1.13)	0.91	0.94 (0.86, 1.03)	0.18
Magnesium, mg/d	1.14 (1.05, 1.24)	0.003	1.09 (0.99, 1.19)	0.09	1.18 (1.10, 1.26)	<0.001[3]
Calcium, mg/d	0.74 (0.69, 0.79)	<0.001[3]	0.67 (0.61, 0.74)	<0.001[3]	0.75 (0.69, 0.81)	<0.001[3]
Sodium, mg/d	1.15 (1.05, 1.26)	0.01	1.18 (1.08, 1.28)	<0.001[3]	1.27 (1.18, 1.37)	<0.001[3]
Potassium, mg/d	1.12 (1.02, 1.22)	0.02	1.05 (0.96, 1.15)	0.28	1.12 (1.05, 1.20)	0.001[3]

[1] Mean bias is the relative intake between reported and consumed foods, calculated as a ratio. Mean bias >1 indicates overestimated intake and mean bias <1 indicates underestimated intake, on average.
[2] Simultaneous entry and photo-assisted recall are app-based food capture methods.
[3] Remains significant after a Bonferroni adjustment for 17 multiple comparisons.

underestimation of intakes of vitamin E and calcium. In the photo-assisted recall group, only added sugars and sodium were overestimated and calcium was underestimated. However, the accuracy of self-reported nutrient intake was similar between app methods. More importantly, with the exception of added sugars and total fat, both app methods produced nutrient profiles comparable to those produced by interviewer-administered, multiple-pass 24HR, the method recommended by ADOPT (Accumulating Data to Optimally Predict obesity Treatment) for capturing usual dietary intake (42, 43). These results are promising and confirm that dietary information typically obtained by traditional, validated methods may be captured with a similar level of accuracy by carefully designed apps that are integrated with easy-to-use features for portion size selection and comprehensive food databases (i.e., databases with a variety of food types, brand name and generic items, and options for food preparation). In addition, these findings reinforce the value of image-assisted recall and the potential for image capture to replace record-assisted recall or assist in same- or next-day recall in the event that immediate food logging is not

TABLE 3 ANOVA for estimated mean bias between reported and consumed foods across food capture methods in completers[1,2]

	Simultaneous entry/photo-assisted recall		Simultaneous entry/24-h recall		Photo-assisted recall/24-h recall	
	Relative mean bias (95% CI)	*P* value[3]	Relative mean bias (95% CI)	*P* value[3]	Relative mean bias (95% CI)	*P* value[3]
Energy, kcal/d	1.05 (0.92, 1.19)	0.65	1.16 (1.02, 1.32)	0.02	1.10 (0.97, 1.25)	0.18
Carbohydrates, g/d	1.07 (0.93, 1.23)	0.54	1.14 (0.99, 1.31)	0.09	1.07 (0.93, 1.23)	0.53
Added sugars, g/d	1.06 (0.82, 1.38)	0.84	1.97 (1.51, 2.56)	<0.001[4]	1.85 (1.42, 2.40)	<0.001[4]
Fiber, g/d	1.09 (0.93, 1.27)	0.41	1.02 (0.87, 1.20)	0.94	0.94 (0.80, 1.10)	0.61
Total fat, g/d	1.05 (0.90, 1.23)	0.74	1.39 (1.18, 1.63)	<0.001[4]	1.32 (1.12, 1.55)	<0.001[4]
Saturated fat, g/d	1.04 (0.89, 1.22)	0.84	1.12 (0.95, 1.31)	0.22	1.08 (0.92, 1.26)	0.52
Protein, g/d	1.01 (0.90, 1.15)	0.96	0.93 (0.82, 1.05)	0.31	0.91 (0.81, 1.03)	0.19
Vitamin A, μg/d	1.10 (0.94, 1.30)	0.32	1.16 (0.99, 1.36)	0.08	1.05 (0.89, 1.23)	0.76
Vitamin C, mg/d	1.02 (0.86, 1.22)	0.94	1.23 (1.03, 1.47)	0.02	1.20 (1.01, 1.43)	0.04
Vitamin D, μg/d	0.96 (0.79, 1.17)	0.89	0.93 (0.76, 1.14)	0.67	0.97 (0.79, 1.18)	0.92
Vitamin E, mg/d	0.91 (0.72, 1.14)	0.57	0.80 (0.64, 1.00)	0.05	0.88 (0.70, 1.10)	0.35
Folate, μg/d	1.10 (0.94, 1.29)	0.32	1.05 (0.90, 1.24)	0.70	0.96 (0.82, 1.12)	0.80
Iron, mg/d	1.00 (0.84, 1.18)	>0.99	1.07 (0.90, 1.26)	0.61	1.07 (0.91, 1.27)	0.60
Magnesium, mg/d	1.05 (0.91, 1.20)	0.69	0.97 (0.84, 1.11)	0.83	0.92 (0.80, 1.06)	0.34
Calcium, mg/d	1.10 (0.96, 1.26)	0.23	0.98 (0.86, 1.13)	0.96	0.90 (0.78, 1.03)	0.13
Sodium, mg/d	0.97 (0.85, 1.12)	0.90	0.90 (0.78, 1.04)	0.18	0.92 (0.80, 1.06)	0.38
Potassium, mg/d	1.06 (0.93, 1.22)	0.54	0.99 (0.87, 1.14)	0.99	0.93 (0.82, 1.07)	0.45

[1] Relative mean bias is the comparison of mean bias between each pair of food capture methods, calculated as a ratio.
[2] Simultaneous entry and photo-assisted recall are app-based food capture methods.
[3] *P* values and 95% family-wise confidence levels are shown from ANOVA with Tukey honest significant difference post-hoc tests.
[4] Remains significant after a Bonferroni adjustment for 17 multiple comparisons.

feasible. Given the widespread acceptability and convenience of technology-based nutrition tools (3, 9, 14, 44), apps designed for dietary data capture also may come with the added benefit of enhanced user reach and engagement.

The comparable accuracy of PIQNIQ to the interviewer-administered 24HR may reflect its incorporation of features that mirror those of the traditional method. For example, the portion size selector Figwee (41) can be considered a technological counterpart of the Food Amounts Booklet used for 24HR. In addition, PIQNIQ's manual image capture feature, which serves as a memory aid for recalling consumed foods (21), is a visual take on the nonleading prompts employed by 24HR. These and other features, packaged in a streamlined interface, make PIQNIQ a promising candidate for eventual use as an accurate diet-tracking tool. Other features to consider while developing or refining diet and nutrition apps include prompts that facilitate recall (15, 26), speech-to-text functionality (45), image recognition (24, 46), and—where user engagement is critical (e.g., weight loss interventions)—personalized feedback or notifications (18). While these features were not evaluated in the current study, they may help address limitations of self-report by creating a customized, user-friendly, and convenient interface for entering granular data.

Our study also suggests that technology tools such as diet-tracking apps should be linked with comprehensive and easy-to-update food composition databases (29). As noted, PIQNIQ was built around FNDDS, so nutrient values from app-sourced data were calculated using FNDDS food codes; meanwhile, nutrient values for study-provided foods were calculated using NDSR food codes. While the accuracy of self-reported data was comparable across app groups, added sugars and total fat were highly overestimated by both methods compared with estimations by 24HR. As described in this report, an adjustment was applied to account for database differences. Although this adjustment may have mitigated some of the potential discrepancy between app-reported and consumed foods, it does not account for the variability in food code choices at the individual level. Often, FNDDS and NDSR included very similar choices for study-provided foods, with many almost identical in composition. However, for items such as meats or vegetables, food preparation defaults may have contributed to database discrepancies; for example, FNDDS may default to a food preparation with added salt or fat, while NDSR may allow the user to choose a specific preparation. Another difference between databases may result from fewer options of certain foods. For example, drained, canned sweet potatoes, a provided menu item, could be chosen through NDSR but not FNDDS (the latter only includes the option of canned sweet potato with sweetened liquids, which has more added sugars). Alternatively, the participant may have chosen a default of candied sweet potatoes, which, depending on portion size estimation, could result in widely different amounts of added sugars in reported compared with consumed values. These issues suggest the need for expanded food databases with consistent food codes that incorporate flexibility to account for food preparation methods in the development of diet and nutrition apps and, more broadly, in health and nutrition research. FoodData Central, which houses the USDA's 5 major food and nutrient databases, is a step in the right direction: by creating a data system with distinct data types, FoodData Central is equipped to serve the goals of researchers, policy makers, academicians and educators, nutrition and health professionals, product developers, and more (47).

Beyond database differences, participants' interpretations of food preparation, ingredients, or characteristics may have affected our results. For example, participants may have erroneously recorded menu items as sweetened rather than unsweetened versions (e.g., sweetened compared with unsweetened applesauce), or chosen recipe-like options rather than simpler ones (e.g., candied sweet potatoes compared with canned sweet potatoes). In these examples, the food code selected may not have been the closest match to the provided food and may have contributed the observed differences in reported compared with consumed values of added sugars. Such choices also may have contributed to the observed overreporting of some nutrients in the app groups. In addition, food items were provided without labels or descriptions, which may have contributed to some of the participants' varied selection of database food items. However, this blinded design reflects real-world settings in which food items are typically unlabeled and details on preparation or other specifics are limited (e.g., restaurants).

Limitations of the current study include its short duration, design-related constraints of the app, and participant characteristics. Notably, the backend of PIQNIQ was not designed to distinguish between data input via manual entry or the default portion size selector. Therefore, the accuracy of the portion size selector could not be quantified, although qualitative data were promising: 98% of app participants reported using the portion size selector, and of those who also used manual entry, 81% preferred the former. In terms of participant characteristics, our study population trended younger, female, white, and not Hispanic or Latino. Further, most participants completed postsecondary education and all were without obesity [individuals with BMIs $\geq$30 were excluded to minimize reporting bias, as obesity is associated with underreporting of dietary intake (48, 49)]. These factors, especially participant education level and BMI [which are not representative of the US population] may limit the generalizability of the study findings and should be considered when designing future studies.

Strengths of the present study include a very low attrition rate (2.3%) as well as complete data for 98% of participants. An additional strength was use of the provided-food protocol with weighed-back adjustment of uneaten foods, which documented actual consumption of study-provided foods rather than using another error-prone method for comparison.

Provided food was chosen as the reference standard because it was most appropriate for accomplishing our objectives, which involved the validation of both energy and nutrient values. However, future studies validating the app also should include an objective biomarker for assessing true energy intake over a longer period (2, 30). In addition, it will be important to assess the accuracy of dietary intake using the app in an environment in which participants self-select their food and nutrient intake to identify possible improvements in estimated nutrients or other sources of error that may result with greater food variety.

Conclusions

This single-site randomized trial testing the accuracy of PIQNIQ, a novel app designed to capture dietary intake, showed that simultaneous entry and photo-assisted recall methods had similar accuracy. Further, nutrients captured by the app, with the exception of added sugars and total fat, were highly comparable to those collected by traditional 24HR. Our findings underscore the importance of developing and enhancing technological tools for dietary assessment. Such tools have the potential to replace traditional methods, which are burdensome to both investigators and respondents, while better engaging the general public.

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