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Applied nutritional investigation

The use of a food logging app in the naturalistic setting fails to provide accurate measurements of nutrients and poses usability challenges

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A B S T R A C T

Objective: MyFitnessPal is the most popular commercial nutrition weight loss app. The aim of this study was to assess how individuals in naturalistic settings performed when recording their dietary intake in MyFitnessPal, and their usability experiences with the app.
Methods: Adults not regularly using MyFitnessPal (N = 43) logged their dietary intake in the app for 4 consecutive days and completed two researcher-administered 24-h recalls collected based on the Automated Multiple Pass Method. Food items from 24-h recalls were coded into food categories and foods omitted from corresponding MyFitnessPal records were calculated. Comparative validity of energy and macronutrient outputs from MyFitnessPal were compared against 24-h recalls using paired *t* tests. Inductive thematic analysis was applied to app usability responses.
Results: Individuals omitted a mean of 18% (SD, 15) of food items, particularly energy-dense and nutrient-poor foods from MyFitnessPal records. Relative to 2-day 24-h recalls, 4-day MyFitnessPal records significantly underestimated mean energy intake by 1863 kJ (SD, 2952 kJ, $P = 0.0002$) and intake of all macronutrients. Although 80% of participants rated MyFitnessPal as easy to use, only 20% said they would continue use, citing challenges in matching foods, estimating portion size, and logging being time-consuming, as affecting motivation for long-term use.
Conclusions: Large discrepancies in nutrient measurements from MyFitnessPal indicate suboptimal performance with using the app to record intake, particularly given food omissions in records and difficulties encountered with app usability relating to the food database and input of portion sizes. Stand-alone use of MyFitnessPal is therefore cautioned and guidance from dietitians is necessary to support use of nutrition apps in collecting accurate dietary data.

Introduction

In 2017, 78 000 new mobile health (mHealth) apps were added into major app stores, taking the total of commercially available mHealth apps to 325,000 [1], With 603.7 million adults estimated to be obese worldwide in 2015 [2], the growth in mHealth apps reflects attempts to develop solutions to address the escalating burden of disease. Smartphone diet-tracking nutrition apps are commonplace in commercial app stores [3], with the majority being calorie counters that are marketed as tools for weight loss [4]. Calorie Counter by MyFitnessPal is the most popular diet-tracking weight loss app in Western countries [3,5], boasting >165 million users [6]. It is also the most common nutrition app recommended by dietitians in Australia, Canada, New Zealand, the United Kingdom, and the United States [7–9]. The MyFitnessPal app provides individuals with a medium to log their food intake and monitor the energy and macronutrient content of their meals against personalized weight loss targets.

Before technological advancements, individuals kept paper-based logs and relied on calorie counting books to calculate energy

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and macronutrient intake. For those who received dietetic care, dietitian-led diet histories, 24-h recalls, or detailed dietary records would be completed. These traditional dietary assessment methods were burdensome for both individuals and dietitians and subject to memory bias and misreporting [10]. Mobile phone technologies may address such limitations [11], given their ubiquity [12] and accessibility even at meal times [13], allowing individuals to log dietary intake in near real time. Individuals also have greater acceptability and preference for recording dietary intake using apps over written paper records [11,14–16]. The capacity to automatically code and quantify energy and macronutrient intake from within nutrition apps is appealing for individuals who want insight and immediate feedback on the composition of their diet in their naturalistic setting, and in a manner independent of dietetic input [5].

How energy and macronutrient outputs from apps compare with dietary assessment methods, such as 24-h recalls or measured energy expenditure, has been investigated, albeit predominately in researcher-based nutrition apps [17–22]. One pioneering study has assessed the accuracy of energy-intake calculations of commercial nutrition weight loss apps, of which MyFitnessPal was included, against the gold standard weighed food record [4]. However, as the researcher had a dietetics background, the findings may not be generalizable to the public that does not possess the same degree of food knowledge. Other studies investigating the comparative validity of commercial nutrition apps have focused on determining the accuracy of the app's food composition database, with researchers entering recall data into the app for comparison [23], or allowing participants the opportunity to go back to correct and log missing food items after the recording period [24]. However, as MyFitnessPal is designed to be a consumer-oriented app, further exploration of the comparative validity of its nutrient outputs when used by members of the public in a naturalistic state and setting is warranted.

A small number of qualitative studies have been conducted among individuals in community or naturalistic settings to understand user experiences and preferences using commercial nutrition apps, including MyFitnessPal as a food record and for weight management [24–26]. Although these apps were generally liked, a range of design features, usability aspects, and factors for facilitating behavior change for weight loss were identified as needing further development. Therefore, this study aimed to assess how individuals in naturalistic settings performed when recording their dietary intake in MyFitnessPal, as well as to explore their usability experiences with the app.

Methods

Participants and recruitment

The Institutional Human Research Ethics Committee granted approval for this study. Recruitment methods included announcements during lectures and social media posts and posters across one Australian university campus and outside community containing a link to the online screening survey. The screener collected participant consent, basic demographic data, and app-use habits.

Eligible participants were >18 y of age, owned a smartphone compatible with MyFitnessPal (iOS or Android), and spoke English. Individuals who were regular users of MyFitnessPal (defined as logging into the app more than three times a week in the past 6 mo) or had formal nutrition education were excluded. These exclusion criteria were implemented as individuals with familiarity with using the MyFitnessPal app or possessing knowledge of nutrition might bias the results in favor of the app, characteristics that would not be representative of use by the general public. As an incentive to participate, a draw to win one of two $20 iTunes/Google Play vouchers, was offered to study completers.

Based on Liao's guidance for sample-size calculations for agreement studies between two measures, at an alpha of 0.05 and beta for power of 0.9, with assumption of no discordant pairs of measurements, a minimum of 45 participants was required for the study [27].

Study design

MyFitnessPal

MyFitnessPal includes an electronic dietary record that allows users to search and log specific branded and generic food items. Energy and macronutrient data outputs from the app are primarily derived from the US Department of Agriculture (USDA) food composition database [28], as well as crowd-sourced data [4]. The app also offers the "create food" option to add custom foods and meals, as well as manually entering nutrient profiles of new foods not present in the database.

Specific instructions on how to download MyFitnessPal, enable the "Diary Sharing" feature, and add researchers as "Friends," were emailed to participants. Participants were instructed to record their intake in the app for 4 days consecutively, including all meals, snacks, and beverages. They received minimal further instruction on how to best use the app, to reflect conditions users in the naturalistic setting would experience when independently downloading the app. With queries about entering composite dishes, participants were told to choose a generic food item that best represented their dish, or to enter individual food items to compose the dish. Energy and macronutrient intake data for each user was gathered at the end of the logging period through accessing participants' MyFitnessPal dietary record data via the "Friends" function.

24-h recalls

Participants were contacted on two random, unannounced occasions (including weekends) within the 4-day logging period to perform 24-h recalls as a reference standard. At the beginning of the recall, participants were reminded not to refer to their dietary record in the MyFitnessPal app (either as a prompt or to aid recall), and to solely rely on their memory.

The National Cancer Institute Automated Self-Administered (ASA24)-Australia [29] was used by one dietetics researcher to conduct 24-h recalls with participants over the phone. The ASA24 [30] is based on the USDA Automated Multiple Pass Method (AMPM) [31] and is a validated 24-h recall tool for assessing dietary intake [32]. The ASA24-Australia uses nutrition information from the Australian Food, Supplement and Nutrient Database (AUSNUT) 2011–2013 [33]. Recall data for 31 participants were exported directly from the ASA24 researcher portal for analysis. These data were combined with a further 16 individuals whose recalls were conducted by a second researcher using the AMPM based on the ASA24, but manually coded. Manual coding of these recalls in FoodWorks8 (Xyris Software) [34] using the AUSNUT 2011–2013 database was required as the ASA24-Australia was not yet available at that stage. Participants were asked to refer to a provided food model booklet [35] to assist with estimation of portion sizes during recalls. Where participants were unsure, the median portion size was used as a starting point for adjustment.

After the 4-day logging period, participants rated the usability experience of MyFitnessPal in an online survey adapted from the System Usability Scale [36] and could provide further feedback via an open-ended response question.

Data analysis

Only the data from participants with $\geq$1 d of MyFitnessPal records and corresponding day 24-h recalls were included for further analysis. All food items from 24-h recalls were coded into food categories and matched against items present in MyFitnessPal records for corresponding days. The total numbers of items omitted by MyFitnessPal per food category and overall were determined. Where participants created a food or entered a generic mixed dish or composite food item in MyFitnessPal (e.g., chicken schnitzel wrap), it was presumed to contain all ingredients reported in the 24-h recall (e.g., wrap, chicken schnitzel, coleslaw, cheese).

Group means for energy and macronutrient (protein, fat, carbohydrate, and sugar) intakes were calculated for both methods. Paired *t* tests were conducted on normally distributed data (or Wilcoxon paired signed-rank test for nonparametric data) to compare the combined means of 2-day records between the two methods. Associations between the two methods were determined using Pearson's product-moment correlation coefficient (or Spearman's rho for nonparametric data). Bland–Altman plots were constructed to assess the agreement between MyFitnessPal and 24-h recalls for the mean intakes of energy and macronutrients for both days [37]. Repeated measures analysis of variance (ANOVA) were conducted across the 4-day MyFitnessPal records to examine the possibility of respondent fatigue. All data was included for these analyses. Sensitivity analysis was carried out on data that excluded under-reporters, identified using Goldberg's cutoffs on 24-h recall data [38], to determine if there were any differences in findings. IBM SPSS Statistics, version 22 (IBM Corp, Armonk, NY, USA) was used to conduct all statistical analyses.

App usability survey responses were coded as positive (*strongly agree* or *agree*) or neutral/negative (*neutral, disagree, and strongly disagree*) for descriptive analysis. Major themes from the open-ended responses were coded using inductive thematic analysis.

Results

From 96 expressions of interest, 21 did not meet eligibility criteria (Fig. 1). Twenty-eight eligible participants failed to respond to follow-up emails, either withdrawing before commencing or during the 4-day logging period, mainly citing time constraints. The 47 participants (9 men) who completed at least 1 d of MyFitnessPal records and a 24-h recall for the same day were included for further analysis. All but 2 of the 47 participants had MyFitnessPal records corresponding to the 2 d of recalls. Forty-three participants completed the full 4-day recording period for MyFitnessPal and the 2-day 24-h recalls. The mean age of participants was 32 y (SD, 14), with 16 participants (34%) >30 y of age. Mean body mass index (BMI) was 24.5 kg/m^2 (SD, 4.7), with 32 participants (68%) in the healthy weight range.

From the 24-h recalls of 47 participants, a mean of 18% (SD, 15%) of food items were omitted per individual from their corresponding MyFitnessPal records. Across all participants, 1445 food items were recorded, of which 271 (19%) were missing from corresponding MyFitnessPal records. Fig. 2 displays the proportion of food items omitted from MyFitnessPal records by different food categories, with fats and oils, alcohol, discretionary foods and beverages (high in fat and/or sugar), and condiments more commonly omitted.

Ten participants were under-reporters based on Goldberg cutoffs. However, as exclusion of under-reporters did not alter the significance of findings, the results presented are for the full data set of participants. Mean energy and macronutrient intake values gathered from the 2 d of recalls and corresponding day MyFitnessPal records, as well as the complete 4-day MyFitnessPal and 2-day 24-h recall records, are displayed in Table 1. Significantly lower values were derived from MyFitnessPal than from 24-h recalls for energy and all macronutrients. Notably, a mean energy-intake difference of −1863 kJ (SD, 2952 kJ, $P = 0.0002$) existed between 4-day MyFitnessPal and 2-day 24-h recall records. Correlation coefficients for energy and macronutrients ranged from negligible to low ($r = 0.21–0.42$), with significant correlations only observed for protein and carbohydrate in the 4-day MyFitnessPal versus 2-day 24-h recalls (Table 1).

Bland–Altman plots in Fig. 3 depict the agreement between MyFitnessPal and the 24-h recalls for energy, protein, fat, carbohydrate, and sugar intakes. No proportional bias was observed for energy or any of the nutrients; however, wide limits of agreement were observed. For differences in energy, six participants had values above the limits of agreement. The repeated measures ANOVA with a Greenhouse–Geisser correction indicated that the mean energy intake across the 4 d of MyFitnessPal records were not statistically significant [$F(2.45, 102.75) = 1.45$; $P = 0.24$].

Of the 47 participants, 1 did not complete the usability survey. The majority of participants (80%) found MyFitnessPal easy to use, indicating that the various functions in the app were well integrated (70%). However, 80% said they were unlikely to continue its use, and 46% of participants indicated that they would recommend the app to others. Slightly more than half of participants (52%) said that food items were easy to find.

Twenty-four participants provided further written feedback on the usability and design features or functions of MyFitnessPal. Four key themes emerged, including insufficiencies in the food database,

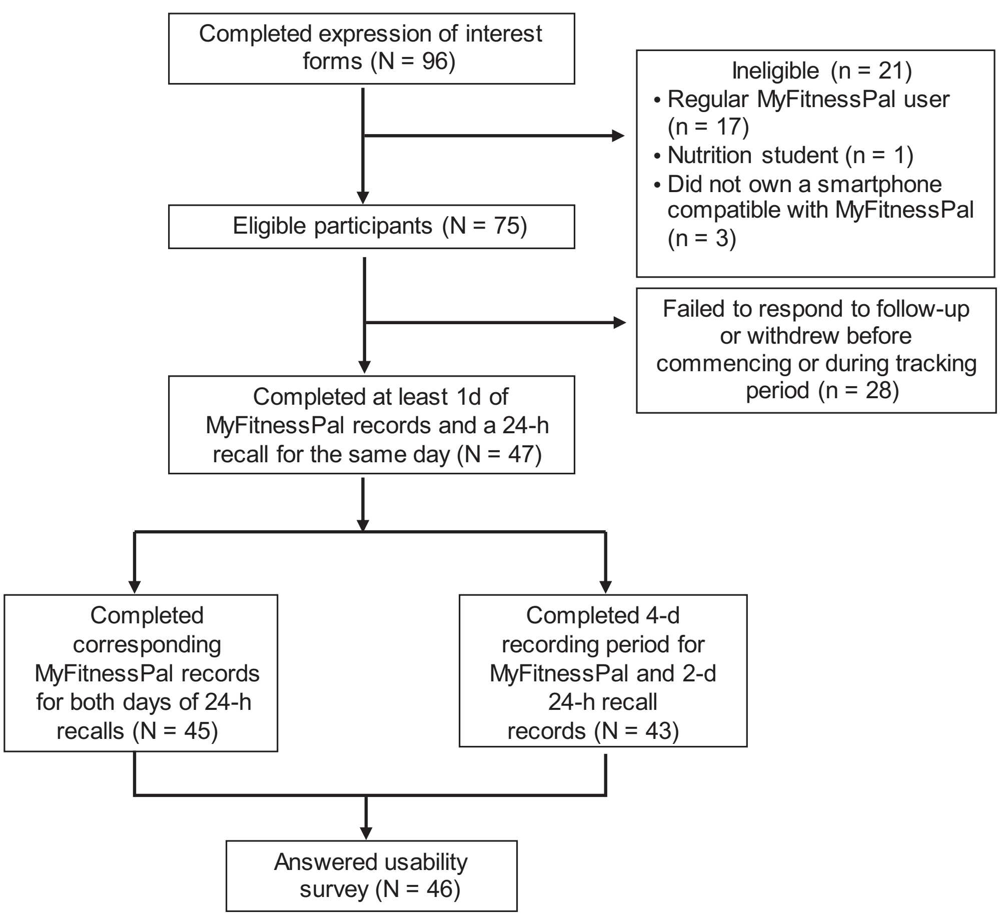

Fig. 1. Participant recruitment flow diagram.

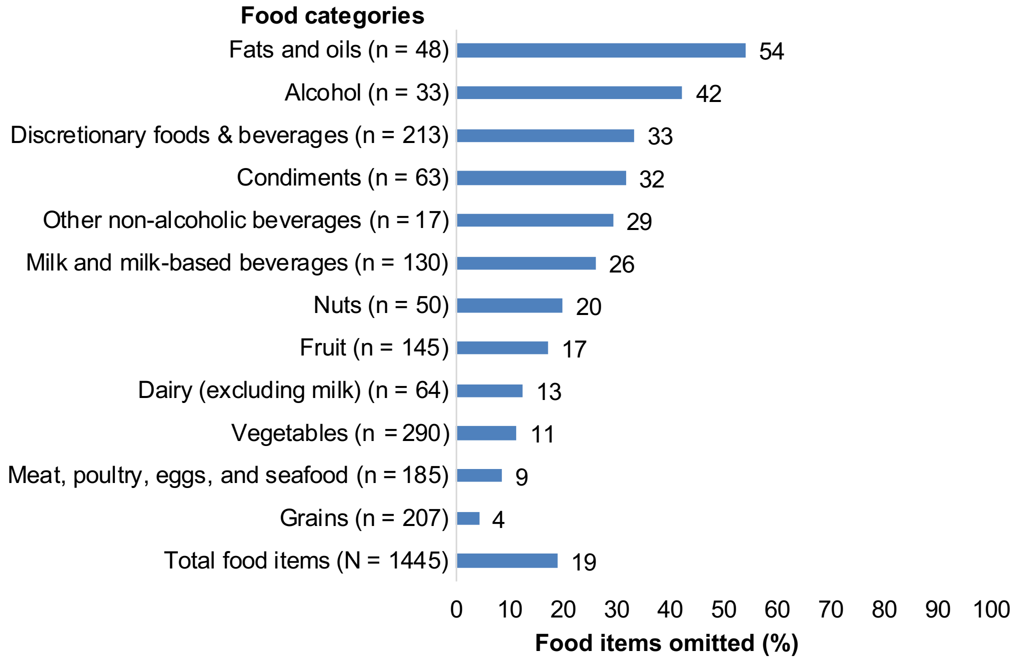

Fig. 2. Foods present in 24-h recalls (N = 47) by food category, but omitted in corresponding day MyFitnessPal records.

confusing portion sizes, time-consuming data entry, and motivational effects. Participants found it difficult to match the exact foods they had eaten to those available in the MyFitnessPal database: "Main issue is the appropriateness and range of food options" (respondent (r)28, male, age 47 y). This led to queries and uncertainties about the accuracy of their selection: "I was never entirely sure if the item I had found in the database was exactly accurate to what I had eaten" (r32, female, age 19 y). For some, the food database was regarded a barrier to recommending the apps to others, with suggestions to include more brands and products from other countries or the option to choose the country of residence for specific results: "It seems to come up with American brands first so it

Table 1
Paired comparisons and correlations of mean energy and macronutrient intakes of the MyFitnessPal (MFP) app vs 24-h recalls (24HR)[*]

	MFP mean (SD)	24HR mean (SD)	Difference MFP − 24HR (SD)	*P*-value	*r*	*P-value*
Day 1 record (N = 47)						
Energy (kJ/d)	6129 (2456)	7926 (2994)	−1797 (3262)	0.0005	0.30	0.04
Energy (kCal/d)	1465 (587)	1894 (716)	−429 (780)	0.0005	0.30	0.04
Protein (g/d)	60 (43)	85 (32)	−25 (39)	<0.0001[†]	0.46[‡]	0.001
Fat (g/d)	44 (27)	75 (34)	−31 (40)	<0.0001[†]	0.20[‡]	0.2
Carbohydrate (g/d)	152 (92)	195 (92)	−43 (99)	0.005	0.42	0.003
Sugar (g/d)	51 (39)	88 (53)	−37 (55)	<0.0001[†]	0.30[‡]	0.04
Day 2 record (N = 45)						
Energy (kJ/d)	6472 (2549)	8322 (2706)	−1850 (3471)	0.001	0.13	0.4
Energy (kcal/d)	1547 (609)	1989 (647)	−442 (830)	0.001	0.13	0.4
Protein (g/d)	63 (39)	92 (40)	−29 (48)	0.0001[†]	0.35[‡]	0.02
Fat (g/d)	47 (29)	77 (29)	−30 (40)	<0.0001	0.04	0.8
Carbohydrate (g/d)	163 (101)	198 (78)	−35 (107)	0.04	0.30	0.05
Sugar (g/d)	54 (44)	86 (44)	−31 (50)	<0.0001[†]	0.25[‡]	0.1
Mean day 1 and day 2 records combined (N = 45)						
Energy (kJ/d)	6330 (2217)	8190 (2622)	−1860 (2900)	<0.0001	0.29	0.05
Energy (kcal/d)	1513 (530)	1958 (627)	−445 (693)	<0.0001	0.29	0.05
Protein (g/d)	61 (36)	89 (34)	−28 (35)	<0.0001[†]	0.43[‡]	0.003
Fat (g/d)	45 (24)	77 (28)	−31 (34)	<0.0001[†]	0.16[‡]	0.3
Carbohydrate (g/d)	158 (90)	198 (76)	−40 (91)	0.005	0.41	0.005
Sugar (g/d)	53 (38)	88 (42)	−34 (45)	<0.0001[†]	0.32[‡]	0.3
MFP 4-d mean vs 2-d mean of 24HR (N = 43)						
Energy (kJ/d)	6263 (2128)	8126 (2642)	−1863 (2952)	0.0002	0.25	0.1
Energy (kcal/d)	1498 (509)	1942 (631)	−445 (706)	0.0002	0.25	0.1
Protein (g/d)	60 (31)	86 (28)	−26 (32)	<0.0001	0.42	0.005
Fat (g/d)	46 (23)	76 (29)	−30 (33)	<0.0001[†]	0.21[‡]	0.2
Carbohydrate (g/d)	158 (88)	199 (77)	−41 (96)	0.007	0.33	0.03
Sugar (g/d)	51 (36)	88 (43)	−37 (47)	<0.0001[†]	0.28[‡]	0.07

[*] Day 1 and 2 records are shown separately, together with the mean of each method from the 2 d combined, and the mean of the 4-d MFP recording period compared with 2-d 2HR.
[†] Wilcoxon ranked test.
[‡] Spearman's rho.

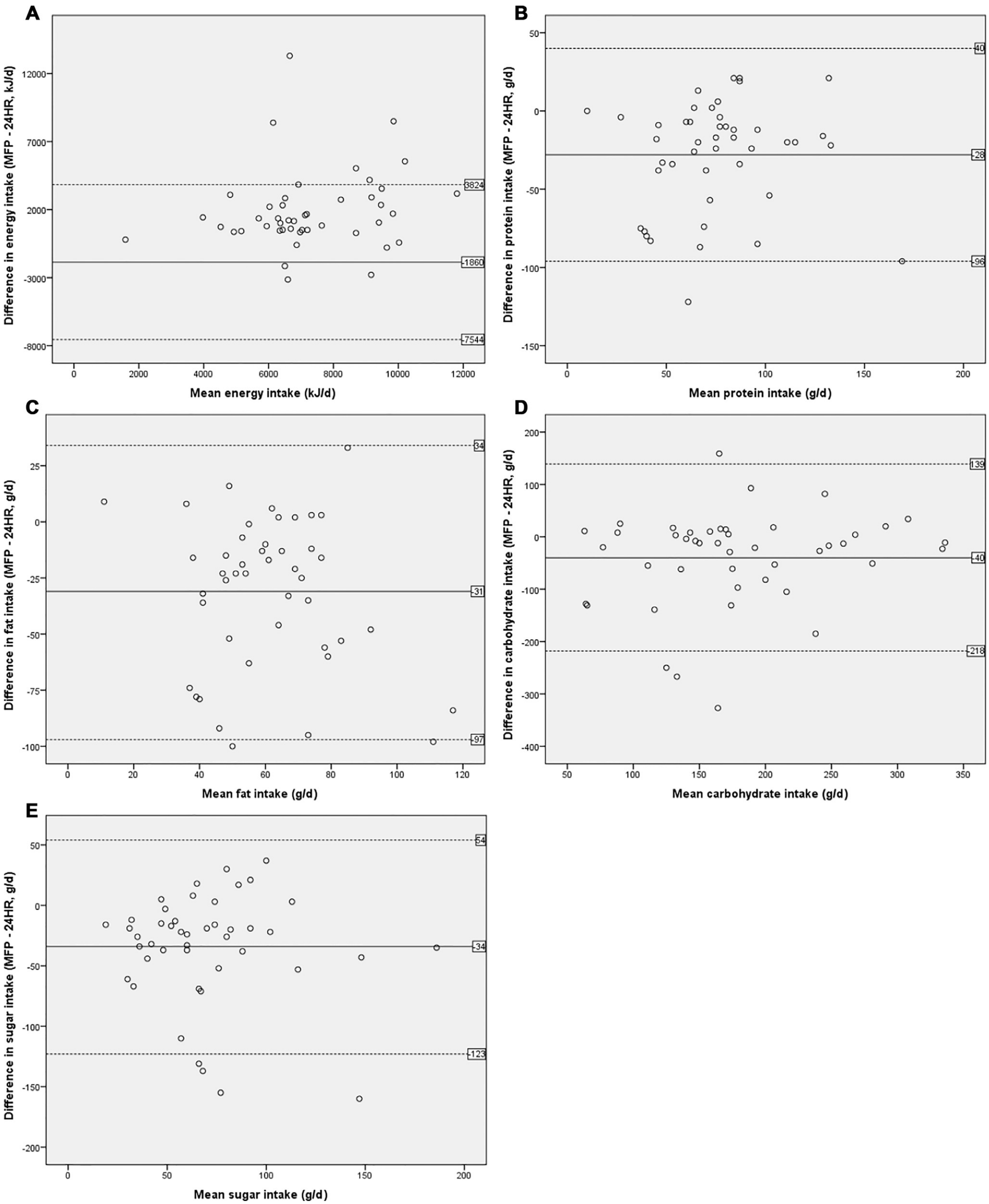

Fig. 3. Bland–Altman plots of MyFitnessPal (MFP) and 24-h recalls (24 HR) from mean day 1 and 2 data, for (**A**) energy intake – mean difference: −1860 kJ; limits of agreement: −7544 kJ to 3824 kJ (**B**) protein intake – mean difference: −28 g; limits of agreement: −96 g to 40 g; (**C**) fat – mean difference: −31 g; limits of agreement: −97 g to 34 g; (**D**) carbohydrate – mean difference: −40 g; limits of agreement: −218 g to 139 g; and (**E**) sugar – mean difference: −34 g; limits of agreement: −123 g to 54 g. Dashed lines indicate the 95% limits of agreement (SD, 1.96) above and below the mean difference (solid line).

would be good to be able to choose a country and have the app automatically place the [country's] grocery store brands closer to the top of generic searches" (r6, female, age 27 y).

Selecting appropriate portion sizes from metric weights (e.g., g, mL) or household measure options (e.g., cups) within the app was challenging for many participants at regular meals, but even more so when eating foods prepared away from home: "Hard to work out how much you ate when you go out for dinner and portions are shared" (r11, female, age 57 y). Informal measures using easily available references, such as the palm of the hand, were suggested to be more helpful: "The amounts were not that easy to use ... It would be beneficial to have more colloquial measurements, like 'handful' or 'size of your palm'" (r15, female, 22 y); as well as portion size pictures: "Maybe they could include some pictures to assist users to quantify how much food they ate (e.g., pictures of bowls/cups)" (r45, female, 19 y).

Although the barcode scanning function made logging packaged foods easier, a key reason cited for not continuing to use MyFitnessPal was because manual data entry was deemed time-consuming and tedious, especially when entering meals with more than a few ingredients or composite dishes with many ingredients: "Logging individual items like a coffee or piece of fruit was fine, but having to put in all the ingredients of a dish separately was tedious and probably not a good representation of the actual dish" (r15, female, 22 y).

It was recognized that in the short term, MyFitnessPal could be a useful tool for motivating users and increasing awareness of energy intake, with some participants even citing weight loss from tracking their intake. However, it was emphasized that the app was not sustainable for long-term use, particularly if detailed recording was required: "I personally wouldn't use the app again or log my food in such detail, but I think with some usability improvements it could be an effective way to monitor someone's diet" (r15, female, 22 y) and "I question the long-term value of the app ... burn out/boredom after initial honeymoon. Very good to encourage a positive 'change' mentality to kick-start a new nutrition program but still need some way to sustain the program" (r7, male, 54 y). For the less tech-savvy, lack of understanding of the range of app functions affected willingness to continue using the app: "As a novice, I didn't realise the range of food items already preloaded, that you could search for. This made entry arduous, and a barrier to ongoing use" (r8, female, 54 y). One participant mentioned that having nutrition professionals' input and accountability could help support using MyFitnessPal: "Having a nutritionist monitor your app...would also be very helpful" (r35, female, 35 y).

Discussion

This is the first study known to have assessed individuals' performance with recording dietary intake in the MyFitnessPal app in their naturalistic setting. Foods most commonly omitted from MyFitnessPal were energy dense and nutrient poor. MyFitnessPal derived energy and macronutrient intake values were consistently lower than those obtained via researcher-administered 24-h recalls. Despite being rated as easy to use, negative usability experiences relating to difficulties with matching food items, estimating portion sizes, and the time-consuming nature of data entry, limited participants' willingness and motivation toward sustained use of MyFitnessPal.

Although apps provide a means for prospective recording, many participants expressed entering meals up to 1 d retrospectively, thus forgetfulness in logging foods and subsequent food omission from MyFitnessPal records were apparent. Consistent with retrospective self-reported dietary assessment [39], foods added to meals or cooking (e.g., fats and oils, condiments), alcohol, discretionary foods and beverages consumed in-between meals, and beverages (milk-based, such as tea and coffee and nonalcoholic, such as black tea and fruit juices) were prone to omission from MyFitnessPal records. As fats and oils and discretionary foods and beverages are typically high in fat, sugar, and energy, the poor correlation observed between MyFitnessPal and 24-h recalls for these nutrients could be explained by the omission of these food categories. The barcode scanner function was appealing for simplifying the logging of packaged foods, consistent with other literature [25,26]. In theory, using the barcode scanner should increase the number of discretionary foods included in dietary records. However, social desirability bias from participants also may have contributed to omission of discretionary and other high-fat and/or high-sugar (i.e., socially undesirable) foods [40].

The commercial popularity of MyFitnessPal indicates large numbers of individuals who download and self-initiate use of MyFitnessPal, often independent of any health professional or dietetic input [9,25]. Marketed as a weight loss app, MyFitnessPal's underestimation of energy intake by 1863 kJ (or 445 kcal) presents substantial clinical implications, given that a 500 kcal/d energy deficit is typically prescribed for weight loss [41]. Of interest, a previous study investigating the use of MyFitnessPal for weight management in the United States found no significant weight loss in the app group at 6 mo [42]. The discrepancy between estimated energy intake in MyFitnessPal and actual intake could compromise weight loss efforts, as individuals may overeat because their energy intake appears below app-recommended targets. However, a previous study reported a difference of only −127 kJ/d (95% confidence interval [CI], −45 to 299 kJ) between MyFitnessPal and 3-day weighed food records kept by a dietitian [4]. Another study found a mean energy-intake difference of −292 kJ/d between MyFitnessPal records entered by a researcher with a dietetics and nutrition background and the data from 30 participants' 24-h recalls collected using a US-based Nutrition Data System for Research [23]. Together, these studies suggest that nutrition knowledge around how to appropriately log foods and estimate portion sizes improves the comparability of app nutrition outputs. Furthermore, when 30 participants were provided with the opportunity to re-enter large missing items from their MyFitnessPal records, only very minor differences in mean energy intake of −56 kJ/d (SD, 852) were observed against paper records analyzed using Brazilian food composition tables [24].

As food logging is the primary function of nutrition apps like MyFitnessPal, the ease of navigating through a food database can affect the quality of dietary data recorded [26]. Large and comprehensive food databases benefit users with variety to choose from [25,26]. However, with nearly half of participants indicating that food items were not easy to find within the app, these usability experiences are consistent with another study finding that although there was a general preference for MyFitnessPal over paper food records, with regard to the ease of recording foods, paper food records were preferred [24]. Moreover, other studies have reporting that crowd-sourced food options in the MyFitnessPal database and the sheer number of foods available can often be overwhelming and compromise accuracy if the incorrect food item is selected [25,43,44]. In fact, incomplete nutrient profiles of many crowd-sourced food options, such as meat-based mixed dishes from restaurants or takeaway joints, is one explanation for the discrepancies particularly in protein intake values between MyFitnessPal records and 24-h recalls.

Furthermore, the food supply of Australia and other European countries, are underrepresented by the predominantly US-based food database of MyFitnessPal [44,45], making it challenging for selecting appropriately matched foods and contributing to error when local nutrition information is not used. Contrastingly, nutrition apps with country-specific food databases reflect greater accuracy [17,18,22]. For example, the researcher-developed app, My Meal Mate, with a UK-specific food database reported a mean energy-intake difference of −218 kJ/d (95% CI, −640 to 201 kJ) between 41 participants' 7-d records and 2-day 24-h recalls [17]. A non-significant mean energy-intake difference of only −34 kJ/d (SD, 2090) was detected between the electronic dietary intake assessment (e-DIA) app using the AUSNUT database and 24-h recalls when validated in young adults in Australia, with similar results found for 24 additional macro- and micronutrients [18] as well as for food groups [19]. Evaluation of a researcher-modified version of the commercial Easy Diet Diary app, with Australian food database, against 24-h recalls found an mean energy intake difference of −268 kJ/d (95% CI, −895 to 358 kJ) between methods, with no significant difference in any other nutrients, except for an underestimation of alcohol [22].

Portion sizes are poorly estimated by individuals [46], and 49% of errors in energy estimations from dietary records administered on personal digital assistants have been attributed to inaccuracies in estimating portion sizes [47]. The inability of participants to estimate how much they consumed using measurement units provided within MyFitnessPal and opting for default portion sizes, were factors contributing to portion size−related-errors. Inclusion of portion size images into an app, such as those available in ASA24 may be a useful tool to support portion size estimation [48], or in recall of portion sizes [49]. New features available in MyFitnessPal include the ability to take photos of meals, which other commercial apps have used to complement dietary records [4,50], and advancements in image-recognition technology and algorithms could potentially support automated estimations of portion sizes [51].

Whereas younger adults are generally more competent with smartphone technologies [52], older individuals may require training from a dietitian about the logging functionalities of MyFitnessPal, which has been effectively used for the validation of other apps [17]. Although older participants had relatively complete records of foods consumed, accompanying energy and macronutrient information was incomplete. Education about the presence of the search bar could prevent the frustration experienced by some older participants at having to "create food" and manually searching up calorie information to input for each food item logged.

Decreased data entry time and more sustained logging of dietary intake are reported strengths of mobile recording [11]. Long-term tracking of diet may be achievable by dedicated users [5], and is associated with greater weight loss [53,54]. Yet, typical engagement with apps, including MyFitnessPal, decreases rapidly over time [16,17,42]. Most participants were compliant with the 4-day logging period in this study and no respondent fatigue was detected in records; however, food logging in MyFitnessPal was perceived to be arduous and time consuming. This was a common sentiment expressed by users of the app, and which ultimately resulted in loss of interest and motivation for using the app long term [26,43,44].

Implications for health professionals

Food omissions and the large underestimation of nutrients by MyFitnessPal, reinforces the importance of health professional, in particular dietetic involvement in guiding the use of these consumer-oriented nutrition apps, especially in weight management. Dietitians, who are the experts in nutrition and managing diets for weight loss, should encourage greater mindfulness and awareness for recording discretionary foods, and continue exercising their expertise and rapport with individuals to probe further about these commonly omitted foods and to verify MyFitnessPal dietary records. Individuals also require education and training from dietitians about the app functions that facilitate more convenient logging of foods and how to more accurately estimate portion sizes. In practice, dietitians should clearly prescribe the period of dietary recording in apps for dietary assessment, so as to maintain patient compliance and minimise possible respondent fatigue that can occur with continued use [55]. Provision of accountability and motivational support from dietitians for more effective engagement with apps is also necessary [56].

Study strengths and limitations

Using 24-h recalls as the reference method is subject to limitations associated with memory and recall bias, yet, very low levels of underreporting by 24-h recalls for many foods and nutrients are actually indicated [57]. To strengthen the accuracy of the recall data, the ASA24 was used to ensure standardized collection of dietary data.

Excluding those with nutrition education and regular MyFitnessPal users enhances the generalizability of the sample to members of the public who may download the app. However, it is important to note that regular users are more likely to represent the motivated members of the public who self-initiate and demonstrate long-term use of MyFitnessPal [5]. It is possible that regular users who have more interest and familiarity with food logging and an understanding of app functions through repeated use, may perform better with logging dietary intake and produce more accurate nutrient measurements. This should be a topic of future study.

Furthermore, participants were not only from the university setting but also from the community. They were also a range of ages, including 30% who were >45 y, which is when onset of many chronic diseases occurs, and when health management tools, such as apps are required. However, there was still a predominance of younger participants, thereby creating potential bias for greater technological literacy. It would be valuable to investigate the use of MyFitnessPal by older individuals and understand their barriers and challenges to use, as dietary management for chronic diseases or weight gain emerges in older age.

Conclusion

Despite its popularity, there was suboptimal performance among individuals with using MyFitnessPal to record dietary intake in their naturalistic setting, as indicated by food omissions in app records and the discrepancies in app nutrition outputs. Stand-alone use of the app is cautioned by app-usability experiences that highlight challenges in navigating the app food database and selecting correct portion sizes. The importance of health professional involvement, such as that of dietitians, is therefore emphasized when using commercial diet-tracking apps, especially for weight management. Future studies should investigate the validity of nutrient measures and individuals' usability experiences with the app when prescribed alongside health professional and dietetic care.

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