Characteristics of smartphone-based dietary assessment tools: A systematic review

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Authors' contributions

LK conceived of the study and developed the research question and search strategy
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27 **Disclosure statement**

28 The authors declare no competing interests.

29 **Data availability statement**

30 A list of all full texts screened and the raw data extracted from the included
31 publications can be obtained from <https://osf.io/xg8s6/>. The search strategy, a list of all
32 extracted information, and a summary of the included data can be found in the online
33 supplement.

Abstract

Smartphones have become popular in assessing eating behaviour in real-life and real-time. This systematic review provides a comprehensive overview of smartphone-based dietary assessment tools, focusing on how dietary data is assessed and its completeness ensured. Seven databases from behavioural, social and computer science were searched in March 2020. All observational, experimental or intervention studies and study protocols using a smartphone-based assessment tool for dietary intake were included if they reported data collected by adults and were published in English. Out of 21,722 records initially screened, 117 publications using 129 tools were included. Five core assessment features were identified: photo-based assessment (48.8% of tools), assessed serving/ portion sizes (48.8%), free-text descriptions of food intake (42.6%), food databases (30.2%), and classification systems (27.9%). On average, a tool used two features. The majority of studies did not implement any features to improve completeness of the records. This review provides a comprehensive overview and framework of smartphone-based dietary assessment tools to help researchers identify suitable assessment tools for their studies. Future research needs to address the potential impact of specific dietary assessment methods on data quality and participants' willingness to record their behaviour to ultimately improve the quality of smartphone-based dietary assessment for health research.

Keywords: Ecological Momentary Assessment, smartphone, mHealth, diet, eating behaviour, dietary assessment

Introduction

In Europe, more than 16% of deaths caused by noncommunicable diseases can be attributed to diet-related risk factors such as consuming diets low in vegetables, fruits or nuts, or diets high in sodium (1). To reduce the risk for noncommunicable diseases and their potential negative outcomes including premature death and reduced quality of life (2), more effective behavioural interventions need to be developed. Health psychology can make important contributions to inform understanding and development of health behaviour change interventions by studying the relationships between psychological determinants, intervention components, and food intake (e.g., Conner et al. (3), Dohle et al. (4), Michie et al. (5)). An important prerequisite for uncovering these relationships is the valid and reliable assessment not only of the determinants and components, but also of the eating behaviour itself.

Most commonly, food intake is assessed using self-reports, such as dietary records, 24-hour dietary recalls, and food frequency questionnaires (FFQ). Their advantages and disadvantages have been discussed extensively in the literature, e.g., (6, 7). To sum, self-reported dietary records are considered the gold standard. They allow every food and beverage to be recorded when it is consumed, often including serving sizes which are determined by weighing. This allows researchers to collect detailed and valid data, however, it also puts a high burden on the study participants. It is thus recommended to only use dietary records for short periods of 4 days or less, which may lead to underestimation of consumption frequency of occasionally consumed foods and limits the generalisability of the collected data (6). FFQs and dietary recalls allow an individual to report multiple meals at once, however, this also means that they rely on the participants' memory and, especially in the context of FFQs, might require them to integrate information from many different eating occasions. This introduces recall bias and thus limits data quality (6, 7).

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Technological advances may resolve some of the limitations of traditional dietary assessment methods while preserving their advantages (8): They allow users to record foods immediately before they are consumed, while at the same time reducing participant burden e.g. by allowing participants to take photos and analysing the content of the photos automatically (9). Smartphones may be especially useful in this regard, since smartphone ownership is common (10), and smartphone owners typically carry their smartphone with them most of the time (11); thus the assessment tool is almost always available. Smartphones are also typically connected to the internet which allows for downloading and uploading information and using additional computing capacity if needed (e.g., for automated image analysis, (9)). Finally, they allow for additional data to be recorded automatically, e.g. timestamps, and using further available sensors, such as GPS (12). Smartphone-based dietary assessment has shown comparable validity to traditional dietary assessment methods (8, 13). Accordingly, smartphones are increasingly used to collect eating behaviour data in daily life (see e.g., (13-16) for reviews).

In health psychology, behavioural data generated from smartphone-based assessments have the additional advantage of enabling the study of not only between-person differences, but also within-person fluctuations and individual differences in the observed effect (17-19). Furthermore, since participants can be surveyed in daily life, smartphone-based assessments may uncover underlying psychological processes of eating behaviour in real-life and real-time. For example, it allows the study of situational influences on eating behaviour (e.g., Franja et al. (20)) and the fluctuations of the behaviour over time (21). This provides researchers with unprecedented opportunities to improve the understanding of the behaviour itself and the precursor-behaviour relationships across time, which may ultimately advance psychological theory and intervention development (22).

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To date, a multitude of smartphone-based dietary assessment tools have been developed for research purposes. However, as previous reviews have already pointed out, these dietary assessment tools differ in many central aspects. For example, researchers may employ time-based or event-based sampling techniques, i.e. whether recordings are completed based on prompts (time-based sampling) or based on manual initiation by the participants whenever an event occurs (event-based sampling (23, 24); see Schembre et al. (14) and Maugeri and Barchitta (15) for overviews). Moreover, smartphone-based dietary assessment tools may differ in the type of data they collect, e.g., consumption of certain food groups (e.g., fruits) or meal types (e.g., breakfasts) (15). Rusin et al. (16) and Pendergast et al. (25) specifically described the data input requested in electronic food diaries, such as providing serving sizes or entering free-text input. However, the field is rapidly evolving and smartphone-based dietary assessment is becoming increasingly popular (26), so it can be expected that more and qualitatively different smartphone-based dietary assessment tools were since published.

The different data input features in smartphone-based dietary assessment tools may strongly impact what data can be recorded and may ultimately influence the conclusions that can be drawn from the studies as well as the comparability of results between studies, and the generalisability of the results to inform practice. For instance, since many nutritional guidelines focus on the amount of foods within particular food groups consumed in a given time period (e.g., 400g of vegetables per day (27)), adherence to these guidelines can only be determined if serving sizes are recorded. Serving sizes can either be recorded directly, e.g. by asking participants to put them into a text field (28), or indirectly, e.g. by estimating them based on photos (29). These portion size assessment methods are susceptible to different potential reporting errors and can reveal differential training needs: if the participant is making the input, estimation errors may be substantial (30), thus participants might need to be

trained to reduce the errors (31). If, on the other hand, if serving sizes are estimated by the research team, variance in the error as well as training costs may be reduced since the coding is typically performed by a small number of people, often with previous experience, e.g. from working as a dietician (32). However, other sources of errors, such as being unable to identify the foods correctly, may be introduced.

Furthermore, different input features may vary in participant burden: Taking a photo is usually perceived as quick and easy, while breaking down the meal into its individual components to search them in a database usually is more burdensome, especially when the food database is very large and correct entries difficult to identify from a long list of options. This may impact both participants' willingness to take part in the study, and the number of records they provide overall (33, 34).

Finally, in addition to offering features to record dietary data, some smartphone-based dietary assessment tools allow participants to add records after a meal has been consumed or to edit recordings after they have been saved, thus allowing participants to reduce reporting errors and improve data accuracy. Again other tools allow information to be added about skipped meals, which may further increase the number of meals of which some information (e.g., consumed, not consumed) is available, and thus improves data completion (33, 35). By ensuring that all relevant data is reported and discrepancies between the normatively expected and actually reported number of meals are reduced (33), data quality can be improved.

To sum, to choose the appropriate dietary assessment tool that fulfils the research aims and objectives, and to ensure quality and validity of the recorded data, and participants' willingness to use the tool, several considerations have to be made (36). For this, an overview of available tools and descriptions of the implemented features for recording food intake is needed. This systematic review aims to address the gap in the literature by providing a

framework for describing smartphone-based dietary assessment tools that can be applied in future research. This framework is a synthesis of descriptions used in the literature; it combines different features that were identified in some previous reviews but not others (e.g., free-text descriptions identified in Rusin et al. (16); food databases identified in Pendergast et al. (25)). This review focuses on smartphone-based assessments in comparison to digital assessment more broadly (14, 15, 25), which allows a focus on more smartphone-specific features such as photo-based recording and automated analysis that may require a connection to a server (9). At the same time, this review includes a broad range of features instead of focusing on one feature only (e.g., Boushey et al. (9) focusing exclusively on photo-based recording). In this vein, the framework systematically describes the different features used to collect data on eating behaviour i.e., food intake or frequency of eating episodes, with smartphones. All smartphone-based assessment tools used for data collection in research were included, independent of information of their validity being available, c.f. Pendergast et al. (25). Furthermore, the framework includes several means for ensuring completeness of the collected data that were presented in individual studies but not yet systematically synthesised; specifically, these features allow records to be amended at a later point in time, adding belated recordings, and recording skipped meals (9, 33). Ultimately, this systematic review aimed to provide an overview of the most commonly used tools to guide researchers in their choice of dietary assessment methodology when planning studies, assisting them to navigate the vast range of smartphone-based dietary assessment tools, contributing to standardised reporting of studies using smartphone-based dietary assessment, and improving such tools in themselves.

Materials and methods

A protocol was developed following the PRISMA 2009 guidelines (37) and preregistered on the Open Science Framework (<https://osf.io/xg8s6/>) prior to conducting this systematic review. This report follows the updated PRISMA 2020 guidelines (38).

Search strategy

An electronic search strategy was developed building upon two previous systematic reviews (14, 15). The search strategy included keywords related to smartphone-based assessment and dietary intake: (“ecological momentary assessment” OR EMA OR “ambulatory assessment” OR “experience sampling” OR “mobile app*” OR “mobile device” OR smartphone) AND (diet OR food OR nutrition* OR nutrient* OR snack* OR “eating habits” OR “dietary habits” OR “dietary assessment” OR “dietary behav*” OR “dietary intake” OR “nutrition assessment” OR “energy intake” OR meal).

The strategy was developed for Pubmed (incl. MEDLINE) and adapted for PsycArticles, PsycINFO, EMBASE, Web of Science Core Collection, IEEE explore database (all from inception to 16th March 2020), and ACM digital library (from 1960 to 16th March 2020). See Appendix A for all search strategies. The initial search in the ACM digital library yielded 4,064 results, however, only 3,969 records could be downloaded. To counteract the reduced number of records from the ACM digital library, Scopus (restricted to publications from the field of Computer Science; from inception to 21st March 2020) was additionally searched¹. Reference lists of all eligible papers were hand searched, and forward citation tracking using Google Scholar was conducted to identify further eligible publications. Moreover, emails were sent to the members’ mailing lists of the European Health Psychology Society, the Society for Behavioral Medicine², the German Psychological Association and the British Psychological Society to identify eligible unpublished work.

Inclusion and exclusion criteria

Any observational, experimental or intervention study using a smartphone-based assessment tools (e.g., apps) for dietary intake or frequency of eating episodes used in

¹ Deviation from the preregistered protocol.

² Deviation from the preregistered protocol.

research settings and published in English was included. In line with Schembre et al. (14) and Maugeri and Barchitta (15), dietary intake was defined as the consumption of foods or food groups (quality and/ or quantity) or energy, micro- or macronutrient intake. Eligible studies may either have assessed all foods and meal types or have focused on specific foods (e.g., fruits and vegetables) or meal types (e.g., snacks). Eligible studies may furthermore have used additional input modalities (e.g., smart-forks), however, only if these were used in combination with a smartphone (e.g., an app to view or transmit the data). To be included, study participants had to be adults of 18 years and older who recorded their own food intake as part of a research project. Studies re-using data from commercial lifestyle apps that were recorded without the users being aware of the data being used in research were excluded; in this case, one can assume that the analysis was a by-product of the dataset being available and the tool might not have been chosen because of its fit in a research setting. Study protocols and design papers were included only if they provided sufficient detail for data extraction. Reviews, meta-analyses and conference abstracts were excluded. In addition, studies were excluded if they (1) assessed psychological characteristics (e.g., emotions) or characteristics of the situation (e.g., availability of food) without assessing dietary intake or frequency of eating episodes, or (2) used self-monitoring of diet only as a behaviour change technique without the aim of analysing the dietary data.

Study selection

All records retrieved from the database searches were imported into Rayyan (39). Duplicates were removed before titles and abstracts were screened independently by two authors, coding articles as provisionally eligible or excluded according to the inclusion and exclusion criteria. Disagreements were resolved by discussion. Afterwards, similarly to title and abstract screening, full texts were screened independently by two authors and coded as

225 eligible or excluded. Again, disagreements were resolved by discussion. A PRISMA flow
 226 diagram documents the flow of records (see Figure 1).

Figure 1. PRISMA flow chart.

227 Data extraction and analysis

228 For all eligible studies, study characteristics and descriptions of the dietary assessment
 229 tools were extracted into a data extraction form (see Appendix B for the full list of data
 230 extracted), including information about the operating system, mobile platform, sampling plan,
 231 and data collected. The features of the dietary assessment tool were coded into five groups,
 232 integrating core features that were determined prior to retrieving records based on
 233 descriptions of digital dietary assessment in several previous reviews (9, 14-16, 25). The
 234 framework describes five core features for collecting dietary data: (1) photo-based
 235 assessment, (2) food database, (3) classification system, (4) free-text description, (5)
 236 assessment of portion or serving sizes. Additional dietary assessment features that could not
 237 be mapped onto these thematic core features were also recorded. Furthermore, it describes

features that can be used to ensure completeness of the recorded data; specifically, the framework includes information on whether participants were able to add belated recordings (33), to record skipped meals (33, 35), or to review and change the records after they were completed (40, 41).

Extraction was performed by one author (LK or SS). A subsample (10% of records) was double-checked for entry errors by a second author (MVE or LK). If data were unavailable, the authors of the primary study were contacted via email. Data were synthesized narratively and tabulated according to key characteristics of the papers and the coding framework of the assessment tools (see Tables 2 and 3, respectively, in Appendix C). Risk of bias was not assessed since this review focuses on the methodology and not the outcome of the studies.

Results

Literature search

A total of 16,733 individual records were screened, of which 3,883 were identified through the ACM digital library. After 16,165 were excluded when screening titles and abstracts, 568 full texts (73 ACM) were screened for eligibility. An additional 16 records were identified through forward and backward citation searches ($n = 13$) and submitted by study authors based on requests sent via mailing lists ($n = 3$). A total of 117 publications were included (see Figure 1).

Study characteristics

The 117 publications were published between 2008 and 2020. The number of publications per year steadily increased (see Figure 2). The majority of publications stemmed from the US (34.2%, $n = 40$), followed by Australia (20.5%, $n = 24$), Germany and the Netherlands (each 6.8%, $n = 8$). Four publications contained two studies (42-45), one

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publication contained three studies (33), and the remaining publications contained one relevant study. Accordingly, 123 studies were included.

Figure 2. Publications per year using smartphone-based dietary assessment.

The majority of these 123 studies were observational studies (76.4%, $n = 94$), while 20 were intervention studies (16.3%), six used data from a larger intervention study (4.9%) and three were study protocols (2.4%). Only a small number of studies restricted recording to certain food groups (e.g., sweets: 11.4%, $n = 14$) or specific meal types (e.g., lunch; 8.2%, $n = 10$), so the majority of studies reported on the full diet. In 68 studies (55.3%), participants used their own smartphone, while in 30 studies (24.4%) the smartphone was provided by the study team. In six studies (4.9%) the participants were provided with a smartphone if they were unable to use their own, and in one study (0.8%), participants used their own smartphones but were provided with a smartwatch. Eighteen studies (14.6%) did not report whether participants were provided with a device. Information about compensation was unavailable for the majority of studies (58.5%, $n = 72$). Typically, participants were compensated with monetary incentives (10.6%, $n = 13$), vouchers (8.1%, $n = 10$) or participation in a raffle (4.9%, $n = 6$) or could choose between two forms of compensation.

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Only two studies (1.6%) explicitly stated that they did not provide any incentive for participation.

Out of the 123 included studies, three used two different dietary assessment tools (33, 46, 47), one study used four different dietary assessment tools (48), and the remaining studies only used one dietary assessment tool each. Accordingly, this systematic review reports on a total of 129 dietary assessment tools that were used by between one and 1027 participants ($M = 73.97$, $SD = 115.04$, median = 46.00, sample size not reported for four studies). The majority of studies used event-based sampling (58.9%), while only 8.5% of studies used time-based sampling. Another 21.7% of studies used a combination of event- and time-based sampling (e.g., event-based recordings of food intake and an evening questionnaire at a fixed time). A further 3.9% of studies used other sampling schemes (e.g., allowed recording once daily, which was initiated by the participant), and 7.0% did not specify the sampling scheme.

The majority of apps were programmed for Android (44.2%/ $n = 57$ Android only, 14%/ $n = 18$ Android and iOS), while 14.7% ($n = 19$) were programmed for iOS only, 1.6% ($n = 2$) for Symbian OS, and 0.8% ($n = 1$) were not restricted regarding operating systems. For one quarter of dietary assessment tools used (24.8%, $n = 32$), the operating system was not reported. The majority of studies used an app that was developed for research purposes (69.2%, $n = 88$), and 23.3% of studies ($n = 30$) used commercial software; 11 studies (8.5%) did not provide any information on the app being custom-programmed or commercial. The most frequently used commercial apps included movisensXS (6.2%, $n = 8$), MyFitnessPal and MealLogger (each 3.1%, $n = 4$).

Features to collect data on food intake and frequency of eating episodes

In the following, studies are described based on the five core features of smartphone-based dietary assessment identified in the literature. Dietary assessment tools often included more than one of the five core features, for instance, a dietary assessment tool may include

both photo-based assessment and free-text description. Results are summarised in Table 2 in Appendix C. Detailed descriptions are provided in Appendix D.

Photo-based assessment

The most frequently used assessment method was taking a photo of the food, used in 63 out of 129 dietary assessment tools (48.8%). Participants were usually asked to take a picture immediately before eating (20, 29, 33, 42, 43, 48-69), but taking a photo was not always mandatory (70, 71). In two studies, participants were asked to fit all foods and drinks in one photo (72, 73), while one study reported that participants were also able to capture additional foods and drinks while eating (74). Two studies also allowed participants to re-use photos that they had taken of previous meals (75, 76). In several studies, participants were asked to take another picture of the leftovers to be able to estimate the amount that was actually consumed (25, 40, 77-83).

Furthermore, some study teams provided specific instructions about how to take the photo to obtain reliable data, such as paying attention to the angle and/or the distance from which the picture should be taken (50, 62, 72, 73, 78, 84). Sometimes participants were asked for a size and/or colour reference, which usually was predefined, such as cutlery (73) or a coin (81), or provided by the study team, such as a reference card as a fiducial marker (25, 54, 60-62, 77, 82). One study allowed participants to use any object with known size that was available (64). One study team also instructed participants not to use the photo-based recording after they had eaten to make up for missed recordings (20) since this would not accurately represent the food that was already consumed. Finally, in two studies, participants were asked to record a short video clip of their food, which could be annotated by a voice recording (85, 86). The photo-based recording was usually implemented in a study app, however, one study used Evernote to record the photos (87).

Photos were usually analysed manually by a trained member of the research team, a nutritionist or a dietician (25, 29, 42, 43, 48, 49, 59-61, 64-67, 72-75, 78, 79, 81-83, 85, 86, 88, 89). Rabbi et al. (44) crowdsourced image-analysis in Mechanical Turk. Other studies automated image-analysis to varying degrees (54). In a small number of studies, image-analysis was semi-automated, e.g. for determining the food's volume (77). Keeney et al. (51) implemented an image-analysis algorithm for the smartphone, which produced an estimated range of calories that could be edited by the participants. Other studies implemented or planned to implement fully automated image-analysis using algorithms, e.g. based on artificial intelligence (53, 56, 57, 76). A small number of studies used the photos to complement other forms of data entry, e.g. as a memory aid for 24 hour recalls (72) or classification into categories (55, 58). Other studies did not report on analysing the food photos (20, 33, 40, 50, 52, 62, 63, 68, 70, 71, 80, 84, 90).

The information extracted from the pictures varied; the majority of the studies used the photos for determining what and/ or how much was eaten (74, 77, 88). Different size references were used for coding including known portion sizes (43), coding manuals (29, 66, 81), reference pictures (82) and menus, if available (73). Different portion sizes measures were used. While some studies conducted a detailed analysis of calories and macro- and micronutrients using food databases such as the US Department of Agriculture (USDA) Food and Nutrient Database or the Australian Food and Nutrient Database (AusNut) and professional software to compute energy, macro- or micronutrient intake (25, 42, 45, 59-61, 67, 75, 82), the remaining studies focused either on weight or the number of portions. One study separated eating episodes into overeating and no overeating episodes (49).

Food database

A food database was used in 39 dietary assessment tools (30.2%). Most studies used food databases supplied by government authorities including the German Nutrient Database,

AusNut, the USDA Food and Nutrient Database or the food database of the Health Promotion Board of Singapore (28, 40, 53, 68, 80, 90-105). Other tools used databases provided by companies, such as MyFitnessPal or LoseIt! (47, 106-113). Yet other studies designed their own databases building on Food Frequency Questionnaires or other checklists (114, 115). Three studies provided no source (71, 116, 117), and one study only used the database to retrospectively correct the output of an image analysis algorithm (54).

Classification system

A classification system to categorise food intake was used in 36 dietary assessment tools (27.9%). Six studies asked participants to classify the food into general categories such as meals vs snacks (74, 118, 119), light vs heavy (120, 121), healthy vs unhealthy meals, or the participants feeling content vs not content (46). However, the majority asked for a classification based on a list of food groups (20, 48, 50, 57, 115, 122-133) that varied in the number of categories presented. For instance, Perez et al. (57) presented participants with five categories (fruits and vegetables; milk and derivatives; fats and sugars; carbohydrates; protein). Elliston et al. (123) provided a list of 13 categories (fruit and vegetables; starchy foods; fish; chips; meat; meat products; poultry; cheese; sweets or chocolates; ice cream; crisps/savoury snacks; cakes/scones/pastry; biscuits). Some used a combination of at least two lists of categories, e.g., first asking for a classification as meal or snack and then proceed with different food groups that were tailored to the meal type (123, 134). Finally, some studies focused on the reporting of one or a few specific food groups (e.g., fruits and vegetables, high fat foods) (135, 136); some others provided participants with a list of foods within one food group and asked which had been consumed (137, 138).

Regarding the presentation of the classification system, most studies used lists with checkboxes or asked participants to select between yes and no for each option on the list (e.g.,

(126)), while some provided icons for every category or food item (50, 55, 56, 58, 137). One study did not provide any information on the classification system used (83).

Free-text description

Participants were asked to provide a free-text description of food intake in 55 dietary assessment tools (42.6%). In most studies, this description was supposed to comprise a list of foods consumed as part of the meal, or ingredients or the food (25, 29, 33, 60, 61, 64-66, 69, 70, 77, 81, 82, 139-145). In addition, some study teams asked participants to report further information such as the number of drinks (139), estimated carbohydrate content (70) or estimated calories consumed (120, 121). Again others asked participants to provide details on cooking methods, brands, and restaurants (60, 61, 146). Six studies allowed participants to provide the description via voice recording (59, 65, 85, 86, 142), which was analysed by speech recognition algorithms (140). However, providing a description was not always mandatory (42). Some studies used the free-text descriptions to complement a provided food database and accordingly only allowed free-text descriptions if the food item was not found in the database (103, 105, 112, 113).

In several studies, the free-text description was used as an aid to analyse dietary intake using food photos or videos, e.g., (85, 86). Typically, analysis was performed manually by the research team (25, 29, 48, 59, 64, 81, 82). Ashman et al. (61) and Chung et al. (75) allowed participants to directly annotate the recorded meal pictures. In other studies, the food description was transferred into professional software with food databases, which was typically performed by dieticians or trained researchers (25, 99, 100, 104). Two of the included studies did not analyse the free-text descriptions (62, 147), and another six of the included studies did not report any information on how the free-text descriptions were recorded or analysed (47, 63, 67, 87, 89, 148).

Assessment of serving or portion sizes

Serving or portion sizes were reported by participants in 63 dietary assessment tools (48.8%). The majority of studies asked participants to estimate serving sizes in grams, ounces or millilitres (47, 48, 83, 91-93, 97, 109, 129, 149) and/ or using common household measures such as cups or spoonfuls (28, 69, 94, 98-100, 102-105, 107, 108, 112, 115, 116, 144, 146, 150). Two studies used a hand measure estimation aid (40, 111). A smaller number of studies used scales such as small, medium and large (96), under- or oversized (48) or more/less than usual (113). Again others asked participants to report the number of items or servings/ standard portions (47, 93, 127, 131, 142, 143), which in some cases could be increased or decreased by tapping a button (128, 137). Wellard-Cole et al. (95) asked participants to indicate the proportion of the plate that the respective food item was covering. Two other studies provided a number of reference pictures to choose from (130, 132). Finally, three studies asked participants to estimate macronutrient or calorie content (71, 89, 151).

Provision of portion or serving sizes was typically used in combination with other features. If participants were asked to provide free-text descriptions, they were sometimes also asked to provide a portion size estimate in the text box (25, 42, 77, 85, 86). Also studies that used food databases often included an estimation of the portion size in the database feature (40, 90, 105, 106). In Ali et al. (150), participants were able to choose from pre-determined portion sizes if they indicated that they consumed foods from certain restaurants that were included in the app. In some studies, providing portion sizes was not mandatory, but only asked for if no other recording (e.g., taking a food picture) was performed (145). To increase accuracy, some studies trained participants in portion size estimation (77, 86, 114), while others provided a scale and measurement cups and spoons (101) or asked participants to weigh the foods before consumption (117). Three studies did not provide further information on the assessment of portion sizes (68, 76, 110)

Other features

Finally, nine assessment tools (7.0%) used other features that could not be assigned to one of the five core features of the coding framework. Two studies included a barcode/QR code scanner to automatically retrieve information on the food product (146, 149). Rabbi, Pfammatter et al. (68) allowed participants to add previously reported meals by providing a history of prior meals. Meule et al. (152) assessed chocolate consumption via a single item measure using a slider from (0) none to (100) a great many. Finally, Chun et al. (147) asked participants to indicate the beginning and ending of any eating activity so that researchers could later segment the jawbone movement recordings into eating and non-eating episodes. Three studies included an end-of-day survey in which a summary of the food intake during the day was also assessed (74, 132, 133). Franja et al. (20) prompted participants at random times during the day, asking participants whether they consumed more, the same or less than usual.

Combination of features

On average, dietary assessment tools included 1.98 of the five core features ($SD = 0.82$, median = 2), ranging from 0 to 4 features. In one study (152), none of the five features were identified. The five most frequent combinations of features were: (1) photo-based recording and free-text descriptions (14.7%, $n = 19$), (2) food database and assessment of serving or portion sizes (13.2%, $n = 17$), (3) photo-based assessment only (11.6%, $n = 15$), (4) classification system only (10.1%, $n = 13$), (5) food database, free-text description, and assessment of serving or portion sizes (8.5%, $n = 11$), see also Table 1.

Table 1. Combinations of features used in the smartphone-based dietary assessment tools.

Photo-based assessment	Food database	Classification system	Free-text description	Assessment of serving or portion sizes	n	%
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x			x		19	14.7
	x			x	17	13.2
x					15	11.6
		x			13	10.1
	x		x	x	11	8.5
		x		x	8	6.2
x			x	x	8	6.2
x		x			7	5.4
			x		6	4.7
x	x			x	6	4.7
			x	x	5	3.9
x		x	x	x	4	3.1
					3	2.3
		x	x		2	1.6
				x	2	1.6
	x	x		x	1	0.8
x	x	x		x	1	0.8

Note. 1 dietary assessment tool did not contain any of the five features and is thus not included in this table.

Features to increase completeness of dietary records

Nineteen dietary assessment tools (14.7%) included the option of reporting meals minutes to hours after they had been consumed, i.e. belated recordings (33, 40, 74, 81). While in most dietary assessment tools assessing the meal in-the-moment of consumption was the default (47), a small number of studies offered participants the option to only record meals once a day, e.g. in the evening (68, 70, 71, 88, 105, 121). Typically, belated recordings had to be completed by the end of the day (47); some studies reminded participants to record any meals or snacks they might have forgotten to assess in an evening report (20, 49, 118, 119, 123, 134).

Only two dietary assessment tools (1.6%) specifically asked participants to record skipped meals. Skipped meals were recorded by pressing a button on the app's home screen (81), and in one case participants were asked to additionally report the type of meal that was skipped (33).

Finally, 25.6% of dietary assessment tools allowed participants to review and/or change the records after they had been assessed (71, 75, 93, 108, 121, 146). For instance, Ladyzynski et al. (142) provided participants with a transcription of the voice recording and asked them to make edits if they spotted mistakes. Similarly, some studies asked participants to review the entry before saving, e.g., because labels were added automatically (51, 54, 90). Two studies limited reviewing and editing to the present day (96, 103), while one study explicitly allowed participants to edit records at any point during the study (110). However, the majority of studies that provided some kind of access to the recorded data provided participants with feedback only, either immediately or at specific points during the study, without an opportunity to edit (40, 42, 46-48, 52, 53, 57, 91, 107, 109, 111-113, 117, 137, 141, 149).

Discussion

Smartphone-based dietary assessment has become popular in health psychology and behavioural sciences to capture eating behaviour in daily life. A multitude of smartphone-based dietary assessment tools has been developed that vary substantially in the implemented features, influencing their suitability for collecting different forms of dietary data. This systematic review presents an overview and comprehensive framework of features used to, first, collect dietary data and, second, improve completeness of the dietary records. This framework can be used to improve understanding and better reporting of smartphone-based dietary assessment tools and ultimately to improve the methodology itself.

Features to collect dietary data

Features used to collect data on food intake and frequency of eating episodes were classified into five core features (photo-based assessment, food database, classification system, free-text description, assessment of serving or portion sizes) which were used either alone or in combination. Photo-based assessment and assessment of serving or portion sizes

were somewhat more common than use of a classification system or food databases to describe what has been consumed. Furthermore, some combinations of features such as combining photo-based recording with free-text descriptions of the consumed foods or the joint use of a food database and the assessment of serving or portion sizes were somewhat more popular than others. However, many different combinations of features have been used to collect dietary data in the field.

This substantial variation potentially leads to the recording of qualitatively different dietary information, e.g., information on the presence of certain food groups in a meal or exact serving sizes in grams. Thus, results from studies using different assessment tools might not necessarily be comparable. Previous systematic reviews have reported some variation in the validity of digital dietary assessment tools including smartphone-based assessments, however, it was not investigated whether this variation was related to differences in included features for dietary assessment (13, 25). For example, validity may be impacted by the required input. Research indicates that people struggle to correctly estimate portion sizes in grams, while they provide more accurate estimations in handfuls (30). Reducing the input required by the user may further improve validity; asking experts such as dietitians to estimate portion sizes from food photos may lead to more accurate estimates than asking study participants to provide the estimates themselves (153).

Although many different smartphone-based dietary assessment tools exist, their validity is only rarely investigated. Overall, their validity seems to be comparable to more traditional dietary assessment methods, and energy intake is often underreported (154). The small number of available validation studies is not sufficient to draw meaningful conclusions about differences in validity based on different implemented features or feature combinations. Moreover, available validation studies use a variety of comparison methods (e.g., direct calorimetry, non-digital self-report measures), which further complicates comparisons of

different validation studies (13, 25). Accordingly, more systematic research on the impact of different features used in smartphone-based dietary assessment tools as well as characteristics of these features on the validity of the recorded dietary data is needed, e.g. by comparing data collected with smartphone-based tools to data collected using dietary recalls, dietary records or even doubly labelled water (e.g., Rollo et al., (155)).

Similarly, smartphone-based dietary assessment tools may differentially impact participants' willingness to take part in research and their willingness and ability to reliably record food intake. For instance, this might impact conclusions about frequency and timing of eating episodes as well as the amount of energy consumed per day (33, 34). A previous review has already outlined potential differences in willingness to use food tracking apps based on the design of features, such as the food database (34). For instance, if the food database is too extensive, searching for the correct food item might be too burdensome. On the other hand, if the food database is not extensive enough, participants might struggle to find an entry that sufficiently describes the food at hand, which might also lead to disengagement (34). This further underlines the importance of providing detailed descriptions of the dietary assessment tool to facilitate readers' understanding of the potential impact the assessment tool might have had on participant retention and missed recordings (13). Finally, recent developments in digital intervention research have shed light on the variety of factors influencing user engagement with digital apps (156), which can also be extended to digital assessment tools for assessing behaviour. When designing digital assessment tools, researchers may want to leverage the opportunities that digital technologies offer to target motivational processes, such as digitalized motivational interviewing and gamification (157, 158), to improve adherence.

Photo-based assessment might generally put less burden on participants than having to provide detailed descriptions or searching for individual food items in a database (13, 32, 33).

To reduce participant burden in providing additional information on the captured meals, two studies allowed participants to voice-annotate a video recording instead of having to describe or search for the food items (85, 86). However, using photo-based recording might be more effortful and resource-intensive for the research team. This trade-off may be alleviated through automated image analysis, i.e. the identification of food items and portion sizes using different machine learning algorithms (32), which has already been used in a small number of studies included in this review (51, 53, 54, 57, 76, 77). Although a large number of research teams are working on automated analysis of food pictures (see e.g., Boushey et al. (9) for an overview), automated image analysis has rarely been tested in field settings. There are several technological challenges that need to be overcome, e.g., image-analysis algorithms typically require more computing power than is available on a smartphone, at least if analysis is expected to be completed within seconds. Some systems therefore outsource image analysis to a server, however, this requires a constant mobile data connection (159). Moreover, especially for volume estimation, automated image-analysis requires multiple photos, or even supplementary data input using a video, which might put an increased burden on the participant (159, 160). Most importantly, however, even though increasingly sophisticated algorithms are employed, the identification of food in an image as well as its classification and the estimation of portion sizes remains a challenge (159, 161). The correct identification of certain food groups such as starchy foods and beverages as well as dishes combining several food groups (e.g., lasagne) is especially difficult (162). It is thus doubtful that automated image analysis alone will be sufficient to generate high quality data on dietary intake, at least in the near future (32).

The present review specifically focused on smartphone-based assessment because smartphone use is widespread in the general population (24). This allows study participants to use their own phone and so reduces the burden of carrying an additional measurement device

(33). However, as Pendergast et al. (25) noted, the field of digital dietary assessment is rapidly evolving. Wearable technology such as smartwatches is increasingly used to capture food intake in daily life. For instance, smartwatches can be used to automatically detect eating-related wrist movements and so trigger an automated recording of the duration of the eating event, or an external assessment of eating behaviour and related variables of interest (see Skinner et al. (163) and Bell, Alam (164) for reviews). Other studies test the use of body-worn cameras or sensors to assess food intake unobtrusively and trigger assessments, e.g., Chun et al. (147); however, most of these sensors have only been used in laboratory settings or small pilot studies, and their accuracy in assessing food intake, especially without additional human input, is still limited (32). Most of the technological advancements regarding automated capturing and analysis of dietary intake so far have been published in outlets from the field of computer science (e.g., Chun et al. (147)), however, it could be expected that they will become more prevalent in behavioural field studies soon (165).

An advantage of smartphone-based dietary assessment compared to using body-worn cameras or other sensors is the opportunity to record determinants or immediate outcomes of food intake such as emotions and cognitions, as well as potential influencing factors on food choice such as the location in which the food was consumed (133, 134). Furthermore, it allows researchers to test interventions in real-life and thus not only evaluate their overall effectiveness, but also their impact on a day-by-day or even decision-by-decision basis (81, 166). Notably, although a large number of studies implemented smartphone-based dietary assessment, e.g. as a self-monitoring tool as part of an intervention, the data was often not analysed. Instead, the effectiveness of the intervention was analysed using more traditional dietary assessment methods such as 24-hours recalls or FFQs. These studies thus miss the opportunity of potentially gaining valuable insights into behaviour change processes over time, e.g. if the change occurs suddenly or in a linear fashion (see Berli et al. (166) for

examples and analytic models). Since smartphone-based dietary assessment may advance not only nutrition epidemiology but also health psychology and public health through advances in behavioural theory (22), the rich datasets should be utilised more efficiently in future research.

Features to improve completeness of dietary records

A second set of implemented features that was synthesised in the present review are features that may improve completeness of the reported data, such as those increasing adherence to reporting. Ensuring completeness of records, i.e. making sure that all consumed foods and drinks are reported for every eating occasion, is crucial to provide an accurate picture of eating behaviour in daily life. To ensure that all records provide accurate data on all foods and drinks consumed, some apps allow users to complete or amend existing records or provide additional information on why no record was provided. The most common feature was to allow participants to review the records and make adjustments if information was missing or false. This was typically used when the input provided by the participant (e.g., photos, descriptions) was analysed by an algorithm implemented in the tool. Participants were presented with the results produced by the algorithm and were able to amend it to ensure accuracy of the recorded information (e.g., Groat et al. (90), Ladyzynski et al. (142); see also Boushey et al. (9)). Other studies also allowed participants to review records that they had completed themselves, however, in many of the included studies no information was provided if this was implemented to improve data quality, or if the records were available, for instance, as part of a self-monitoring/ feedback intervention.

A second issue regarding the completeness of records is whether the eating occasion is assessed at all. A small number of studies therefore allowed participants to report if they had missed recording an eating event. Since event-based recording is the most commonly used sampling scheme in smartphone-based dietary assessment, taking potential missed recordings

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Figure 2: Overview of framework describing the characteristics of smartphone-based dietary assessment.

into account may be crucial for data quality. Especially when using event-based recording, participants might be prone to forgetting to record their food before eating, e.g., because they are distracted by talking to other people (see Ziesemer et al. (33) for a qualitative analysis of reasons for missed recordings in smartphone-based dietary assessment). Allowing participants to add belated recordings can substantially increase the number of reported meals (33, 35). Completeness of records can be further increased by allowing participants to explicitly state that they have not consumed a meal, since distinguishing between missing records and skipped meals is otherwise not possible. Making this distinction explicit in the recording process can be implemented at low cost, but substantially improves data quality (see Ziesemer et al. (33) for a discussion).

Recommendations for using the analytical framework for study planning and reporting

The presented framework may be a starting point for researchers when designing smartphone-based dietary assessments (see Figure 3 for an overview). First, researchers need to decide which features to implement for assessing dietary data. This choice largely depends on the aims of their study. For instance, photo-based assessment, food databases, classification systems and free-text descriptions assess *what* was eaten, while only photo-

based assessment and assessment of serving or portion sizes assess *how much* was eaten. Thus, if researchers plan to analyse energy consumption, both what and how much was eaten is relevant, while information on portion sizes may not be needed to investigate whether certain food groups were consumed at all. Moreover, the level of detail may vary between features. For instance, classification systems usually present participants with different food groups to reduce the number of options, while food databases may contain thousands of entries and so present participants with a range of foods within a food group, and maybe even with additional characteristics such as different cooking methods (e.g., raw carrot, cooked carrot). Again, which feature is most useful depends on the research question: if researchers are interested in studying the consumption of specific food groups, the classification system may be sufficient, but if researchers want to investigate the consumption of different foods (e.g., different types of vegetables and fruit) a food database may be more helpful.

Second, researchers may want to consider implementing features to ensure completeness of the data. On the one hand, they can implement features to ensure that reporting of individual eating occasions is as accurate as possible by allowing participants to review and amend records after they have been submitted. Researchers may also want to make sure that as many eating occasions as possible are actually reported by allowing participants to retrospectively report eating occasions that they missed to log. Lastly, researchers might be interested in knowing whether an eating occasion was not reported or not consumed, which can be revealed by asking participants to record skipped meals.

Furthermore, once a study is conducted, the presented framework can be used to standardise reporting, similar to the Behaviour Change Techniques taxonomy for intervention components (167). Again, following the overview presented in Figure 3, researchers can describe which features were used to collect data on eating behaviour and which features (if any) were included to ensure completeness of the recorded data. Furthermore, researchers

might need to pay attention to describing the data collection and data processing procedure in sufficient detail, since there have been substantial differences between studies. Tables 4 and 5 in Appendix C outline the most common designs for features to assess eating behaviour and features to ensure completeness, respectively, and may serve as a reporting blueprint. The framework will likely need to be extended in the future once more information on the validity and potential impact of the different features are known.

Strengths and limitations

This systematic review provides a comprehensive overview of smartphone-based dietary assessment tools as well as a new framework for describing commonly used features and their combinations. The review draws from a broad range of disciplines within the behavioural, social and health sciences as well as computer science. However, it is important to note that the review is limited to smartphone-based dietary assessment; older technologies such as PDAs or iPods were not included since they lack the facility to up- and download information via mobile data. The review furthermore reports on individual tools, since publications often did not report names of tools or their version or cross-reference to other publications using the same tool or even dataset. It was thus not possible to reliably identify whether several publications reported on the exact same version of a tool. This information would have allowed for drawing more precise conclusions about which tools are most often used in research; researchers should thus carefully report which tool or dataset they used to facilitate comparisons in the future. Moreover, the present review focused on tools that have been developed for adults only. Smartphone-based dietary assessment is also frequently used in children and adolescents (see e.g., Mason et al. (168) for a recent systematic review). However, since especially children may not be able to use certain features such as food databases, and design aspects such as the use of icons and imagery might be different, the focus of this review was kept concise by excluding smartphone-based dietary assessment

tools for children. Finally, the present systematic review does not address validity of the collected data, potential undesired effects of recording on behaviour (e.g., measurement reactivity (169, 170)), features to improve engagement, or usability³ since those are rarely reported. However, it does provide a starting point for the systematic assessment of validity, undesired effects and usability of smartphone-based dietary assessment based on the implemented features. Similarly, the presented framework can be used to quantify the effectiveness of specific smartphone-based dietary assessment tools as self-monitoring interventions to promote eating behaviour change and weight loss (171, 172).

Conclusion

Smartphone-based dietary assessment is increasingly used to capture food intake, its determinants and consequences in daily life and may advance psychological theory through studying within-person processes. The present systematic review provides an overview of which features and combinations of features are most commonly used to capture dietary data and improve its accuracy. It presents a framework for describing the current state of the art in dietary assessment and discusses the challenges related to different measurement techniques. In this vein, it lays the foundation for an improved description of smartphone-based dietary assessment tools in future studies as well as the systematic study of smartphone-based dietary assessment methodology.

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³ Data on user experience metrics were extracted; however, they were only reported for 24 of the included tools. The extracted information can be found in column BH in the raw data file provided on <https://osf.io/xg8s6/>.

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Appendix A – Search strategies

ACM Digital Library

("ecological momentary assessment" OR EMA OR "ambulatory assessment" OR "experience sampling" OR "mobile app*" OR "mobile device" OR smartphone) AND (diet OR food OR nutrition* OR nutrient* OR snack* OR "eating habits" OR "dietary habits" OR "dietary assessment" OR "dietary behav*" OR "dietary intake" OR "nutrition assessment" OR "energy intake" OR meal)

EMBASE

("ecological momentary assessment" OR EMA OR "ambulatory assessment" OR "experience sampling" OR "mobile app*" OR "mobile device" OR smartphone) AND (diet OR food OR nutrition* OR nutrient* OR snack* OR "eating habits" OR "dietary habits" OR "dietary assessment" OR "dietary behav*" OR "dietary intake" OR "nutrition assessment" OR "energy intake" OR meal)

IEEE explore

("ecological momentary assessment" OR EMA OR "ambulatory assessment" OR "experience sampling" OR "mobile app*" OR "mobile device" OR smartphone) AND (diet OR food OR nutrition* OR nutrient* OR snack* OR "eating habits" OR "dietary habits" OR "dietary assessment" OR "dietary behav*" OR "dietary intake" OR "nutrition assessment" OR "energy intake" OR meal)

Pubmed (incl. MEDLINE)

("ecological momentary assessment" OR EMA OR "ambulatory assessment" OR "experience sampling" OR "mobile app*" OR "mobile device" OR smartphone) AND (diet OR food OR nutrition* OR nutrient* OR snack* OR "eating habits" OR "dietary habits" OR "dietary assessment" OR "dietary behav*" OR "dietary intake" OR "nutrition assessment" OR "energy intake" OR meal)

PsycArticles

("ecological momentary assessment" OR EMA OR "ambulatory assessment" OR "experience sampling" OR "mobile app*" OR "mobile device" OR smartphone) AND (diet OR food OR nutrition* OR nutrient* OR snack* OR "eating habits" OR "dietary habits" OR "dietary assessment" OR "dietary behav*" OR "dietary intake" OR "nutrition assessment" OR "energy intake" OR meal)

PsycInfo

("ecological momentary assessment" OR EMA OR "ambulatory assessment" OR "experience sampling" OR "mobile app*" OR "mobile device" OR smartphone) AND (diet OR food OR nutrition* OR nutrient* OR snack* OR "eating habits" OR "dietary habits" OR "dietary assessment" OR "dietary behav*" OR "dietary intake" OR "nutrition assessment" OR "energy intake" OR meal)

Scopus (limited to Computer Science)

ALL (("ecological momentary assessment" OR ema OR "ambulatory assessment" OR "experience sampling" OR "mobile app*" OR "mobile device" OR smartphone) AND (diet OR food OR nutrition* OR nutrient* OR snack* OR "eating habits" OR "dietary habits" OR "dietary assessment" OR "dietary behav*" OR "dietary intake" OR "nutrition assessment" OR "energy intake" OR meal)) AND (LIMIT-TO (SUBJAREA , "COMP"))

Web of Science Core Collection

("ecological momentary assessment" OR EMA OR "ambulatory assessment" OR "experience sampling" OR "mobile app*" OR "mobile device" OR smartphone) AND (diet OR food OR nutrition* OR nutrient* OR snack* OR "eating habits" OR "dietary habits" OR "dietary assessment" OR "dietary behav*" OR "dietary intake" OR "nutrition assessment" OR "energy intake" OR meal)

Appendix B – List of data extracted

Study information

- Title
- First author
- Year of publication
- Journal name
- Geographical setting
- Study design
- Study aim

Information on participants

- Number of participants
- Dropout
- Reasons for dropout
- Inclusion and exclusion criteria
- Age
- Sex/ gender
- Nationality or ethnicity
- Socioeconomic status (e.g., income, employment, education)
- BMI
- Information about current diet
- Any notable information on health status

Information on completeness of data

- Number of assessed meals/ beeps
- Mean number of days with sufficient number of recordings by participant
- Other information on attrition

Information on study design

- Duration of assessment (as planned in study design)
- Duration of assessment: consecutive or nonconsecutive
- EMA design (signal- or event-contingent, mixed, other)
- Description of design

- Compensation

Information on study outcomes

- Outcomes related to dietary intake
- Focus on specific food groups (yes/ no)
- Description of specific food groups
- Focus on specific meal types (yes/ no)
- Description of meal types
- Outcomes related to the frequency of eating episodes

Information on assessment tool

- Name of tool
- Restrictions to devices
- Own device or provided by the study team?
- Commercial platform used (yes/ no)
- Name of the commercial platform

Information on features to collect data on food intake and frequency of eating episodes

- Photo-based assessment (yes/ no)
- Description of photo-based assessment
- Description of analysis of photos
- Automated image analysis (fully/ semi/ not automated)
- Description of algorithm
- Use of a food database (yes/ no)
- Description of the food database
- Use of a classification system (yes/ no)
- Description of the classification system
- Use of free-text description (yes/ no)
- Description of analysis of free-text responses
- Assessment of serving sizes/ amounts (yes/ no)
- Description of assessment of serving sizes/ amounts
- Other means of collecting data on food intake and frequency of eating episodes

Information on features to increase completeness of dietary records

- Possibility to add belated recordings/ addendums (yes/ no)
- Description of belated recordings/ addendums
- Possibility to record skipped meals (yes/ no)
- Description of recording skipped meals
- Possibility to review/ change entries after recording
- Description of reviewing/ changing entries

Other information

- Other notable characteristics of the tool
- Quantitative information about usability

Appendix C

Table 2. Study characteristics

Paper	Country	Number of studies	Number of groups	Study design	Outcomes related to dietary intake				Compensation (categorized)
					Focus on specific food groups?	Description	Focus on specific meal types?	Description	
Aizawa et al. (2014)	Japan	1	1	observational	no	NA	no	NA	not reported
Ali et al. (2017)	UK	1	1	observational	no	NA	no	NA	not reported
Ambrosini et al. (2018)	Australia	1	1	observational	no	NA	no	NA	not reported
Antonio et al. (2018)	USA	1	1	observational	no	NA	no	NA	not reported
Ashman et al. (2016)	Australia	1	1	observational	no	NA	no	NA	feedback
Ashman et al. (2017)	Australia	1	1	observational	no	NA	no	NA	not reported
Béjar (2017)	Spain	1	1	observational	no	NA	no	NA	not reported
Béjar and Vázquez-Limón (2017)	Spain	1	1	observational	yes	fruit; vegetables; legumes; chicken/ turkey; fish; red meat; soft drinks; sweets; prepared foods; alcoholic beverages	no	NA	not reported
Béjar et al. (2018)	Spain	1	1	observational	no	NA	no	NA	raffle
Béjar et al. (2019)	Spain	1	1	observational	no	NA	no	NA	not reported
Biel et al. (2018)	Switzerland	1	1	observational	no	NA	no	NA	money
Boh, Lemmens, et al. (2016)	the Netherlands, Belgium	1	1	study protocol	no	NA	no	NA	not reported

Boh, Jansen, et al. (2016)	the Netherlands	1	1	observational	yes	hamburger; muffin; cookies; candy bar; candy; dish with a side of chips; crisps; pizza; cake; ice cream; salad; apple; sandwiches; pasta; cornflakes; dishes with a side of potatoes; dishes with a side of rice; yoghurt; soup	no	NA	voucher
Bucher Della Torre et al. (2017)	Switzerland	1	1	observational	no	NA	no	NA	not reported
Butscher et al. (2016)	Germany	1	1	observational	no	NA	no	NA	not reported
Carter et al. (2013)	UK	1	1	observational	no	NA	no	NA	use device for study duration
Chaudhry et al. (2016)	USA	1	1	observational	no	NA	no	NA	money
Chen et al. (2017)	Malaysia	1	1	observational	no	NA	no	NA	reimbursement for expenses
Chen et al. (2019)	Australia	1	1	observational	no	NA	no	NA	voucher
Chmurzynska et al. (2018)	Poland	1	1	observational	yes	high fat foods	no	NA	not reported
Chun et al. (2018)	USA	1	1	observational	no	NA	no	NA	not reported
Chung et al. (2019)	USA	1	1	observational	no	NA	no	NA	not reported
Cordeiro et al. (2015)	USA	1	1	observational	no	NA	no	NA	money
Desai et al. (2019)	USA	1	1	observational	no	NA	no	NA	not reported
Elliston, Ferguson, Schüz, et al. (2017)	Australia	1	1	observational	no	NA	No	NA	voucher
Elliston, Ferguson and Schüz (2017)	Australia	1	1	observational	no	NA	no	NA	voucher

Elliston et al. (2019)	Australia	1	1	observational	no	NA	no	NA	voucher
Elliston et al. (2020)	Australia	1	1	observational	no	NA	no	NA	voucher
Falkenberg et al. (2021)	Australia	1	1	observational	no	NA	no	NA	not reported
Franja et al. (2020)	Australia	1	1	observational	no	NA	no	NA	money
Fuchs et al. (2019)	Switzerland	1	1	observational	no	NA	no	NA	not reported
Gatica-Perez et al. (2019)	Switzerland	1	1	observational	no	NA	no	NA	not reported
Gill and Panda (2015)	USA	2	1						
		Study 1	1	observational	no	NA	no	NA	not reported
		Study 2	1	intervention	no	NA	no	NA	not reported
Godfrey (2017)	USA	1	1	observational	no	NA	no	NA	money, voucher
Groat et al. (2018)	USA	1	1	observational	no	NA	no	NA	not reported
Hendrie et al. (2019)	Australia	1	1	intervention	yes	vegetables	no	NA	not reported
Hezarjaribi et al. (2019)	USA	1	1	observational	no	NA	no	NA	not reported
Hongu et al. (2015)	USA	1	1	observational	no	NA	no	NA	not reported
Hsu et al. (2014)	Taiwan	1	1	observational	no	NA	no	NA	not reported
Jung (2017)	USA	1	1	observational	no	NA	no	NA	not reported
Jung et al. (2017)	Australia	1	1	observational	yes	vegetables	no	NA	not reported
Jung et al. (2020)	Australia	1	1	observational	no	NA	no	NA	money
Karway et al. (2020)	USA	1	1	observational	no	NA	no	NA	not reported
Kato-Lin et al. (2015)	USA	1	4	intervention	no	NA	no	NA	money, raffle
Keeney et al. (2012)	USA	1	1	observational	no	NA	no	NA	not reported

Kong et al. (2016)	China	1	1	observational	no	NA	no	NA	not reported
König and Renner (2018)	Germany	1	1	observational	no	NA	yes	lunch	course credit, voucher
König and Renner (2019)	Germany	1	1	intervention	no	NA	yes	lunch	money, course credit
Ladyzynski et al. (2018)	Poland	1	1	observational	no	NA	no	NA	not reported
Leipold et al. (2018)	Germany	1	1	intervention	no	NA	no	NA	none
Lim et al. (2017)	Singapore	1	1	observational	no	NA	no	NA	not reported
Lozano-Lozano et al. (2018)	Spain	1	1	observational	no	NA	no	NA	not reported
Maher et al. (2020)	USA	1	1	observational	yes	fruits; vegetables; fast food; chips or fries; pastries or sweets; whole wheat foods; water; soda or sweet tea; diet soda; energy drink; sports drink; coffee; milk; fruit juice; alcohol	no	NA	not reported
Martin et al. (2012)	USA	2							
		Study 1	1	observational	no	NA	no	NA	not reported
		Study 2	1	observational	no	NA	no	NA	not reported
Mattila et al. (2008)	Finland	1	1	intervention	no	NA	no	NA	not reported
Mattila et al. (2010)	Finland	1	1	observational	no	NA	no	NA	not reported
McCarroll et al. (2015)	USA	1	1	intervention	no	NA	no	NA	not reported
McHill et al. (2017)	USA	1	1	observational	no	NA	no	NA	not reported
McHill et al. (2019)	USA	1	1	observational	no	NA	no	NA	not reported
Mescoloto et al. (2017)	Brasil	1	1	observational	no	NA	no	NA	not reported
Meule et al. (2019)	Austria	1	1	intervention	yes	chocolate	no	NA	money, course credit

Mirtchouk et al. (2017)	USA	1	1	observational	no	NA	no	NA	not reported
Most et al. (2018)	USA	1	1	observational	no	NA	no	NA	not reported
Most et al. (2019)	USA	1	1	observational	no	NA	no	NA	not reported
Mummah et al. (2016)	USA	1	1	intervention	yes	vegetables	no	NA	not reported
Nandy et al. (2019)	USA	1	1	observational data from larger intervention study	yes	fruit and vegetables; sugar-sweetened beverages; desserts and other sweets	no	NA	token, using the study phone
O'Connor et al. (2019)	USA	1	1	observational	yes	chips/ fries; pastries, pan dulce or sweets; fast food; fruits and vegetables; soda and energy drinks	no	NA	gifts
Panza (2018)	USA	1	1	observational	no	NA	no	NA	money
Parr et al. (2018)	Australia	1	1	intervention	no	NA	no	NA	not reported
Pellegrini et al. (2018)	USA	1	1	observational data from larger intervention study	no	NA	no	NA	not reported
Pendergast et al. (2017)	Australia	1	1	observational	no	NA	no	NA	voucher
Pentikäinen et al. (2019)	Finland	1	2	intervention	no	NA	no	NA	not reported
Perez et al. (2015)	China	1	1	observational	no	NA	no	NA	not reported
Poelman et al. (2020)	the Netherlands	1	1	study protocol	yes	fruit, vegetables, snacks, fast food	no	NA	voucher
Rabbi, Pfammatter, et al. (2015)	USA	1	1	intervention	no	NA	no	NA	not reported
Rabbi, Aung, et al. (2015)	USA	2							
		Study 1	1	intervention	no	NA	no	NA	money
		Study 2	1	intervention	no	NA	no	NA	not reported

Rangan et al. (2015)	Australia	1	1	observational data from larger intervention study	no	NA	no	NA	raffle
Rangan et al. (2016)	Australia	1	1	observational	no	NA	no	NA	raffle
Raynor et al. (2019)	USA	1	1	observational	no	NA	no	NA	not reported
Recio-Rodriguez et al. (2019)	Spain	1	1	observational data from larger intervention study	no	NA	no	NA	not reported
Regan et al. (2020)	USA	1	1	observational	no	NA	no	NA	not reported
Richard et al. (2017)	Austria	1	1	observational	no	NA	yes	snacks	money, course credit
Richard et al. (2019)	Austria	1	1	observational	no	NA	yes	snacks	course credit
Robinson et al. (2013)	UK	1	1	intervention	no	NA	no	NA	money
Roefs et al. (2019)	the Netherlands	1	1	observational	yes	hamburger; muffin; cookies; candy bar; candy; dish with a side of chips; crisps; pizza; cake; ice cream; salad; apple; sandwiches; pasta; cornflakes; dishes with a side of potatoes; dishes with a side of rice; yoghurt; soup	no	NA	voucher
Roy et al. (2017)	Australia	1	1	observational	no	NA	no	NA	raffle
Schüz, Schüz, et al. (2015)	Australia	1	1	study protocol	no	NA	no	NA	not reported
Schüz, Bower, et al. (2015)	Australia	1	1	observational	no	NA	no	NA	money
Schüz et al. (2017)	Australia	1	1	observational	yes	Confectionary; Savoury; Fruit/ Nuts; Dairy; Biscuits/ Cake/ Pastries, Fast food; other	yes	snacks	not reported

Schüz et al. (2018)	Australia	1	1	observational	yes	fruit and vegetables; starchy foods; fish; chips; meat; meat products; poultry; cheese; sweets or chocolate; ice cream; crisps/ savoury snacks; cakes/ scones/ pastry; biscuits	no	NA	money
Seitzinger et al. (2019)	Canada	1	1	observational	no	NA	no	NA	money
Seto et al. (2014)	China	1	1	observational	no	NA	no	NA	money
Seto et al. (2016)	China	1	1	observational	no	NA	no	NA	not reported
Simpson et al. (2017)	New Zealand	1	1	observational	no	NA	no	NA	not reported
Skinner (2019)	USA	1	1	intervention	no	NA	no	NA	not reported
Spanakis et al. (2015)	the Netherlands	1	1	observational	no	NA	no	NA	money
Spring et al. (2018)	USA	1	1	observational	no	NA	no	NA	not reported
Stein and Brooks (2017)	USA	1	1	intervention	no	NA	no	NA	intervention
Teixeira et al. (2018)	Brazil	1	1	intervention	no	NA	no	NA	not reported
Tejpal et al. (2019)	UK	1	1	observational	no	NA	no	NA	none
Terzimehić et al. (2016)	Germany	1	1	observational	no	NA	no	NA	not reported
Villinger et al. (2020)	Germany	1	1	observational data from larger intervention study	no	NA	no	NA	feedback
Wahl et al. (2017)	Germany	1	1	observational	no	NA	no	NA	money, course credit
Waki et al. (2015)	Japan	2							
		Study 1	1	intervention	no	NA	no	NA	not reported
		Study 2	1	observational	no	NA	no	NA	not reported

Wang et al. (2018)	USA	1	1	observational	no	NA	no	NA	not reported
Wellard-Cole et al. (2018)	Australia	1	1	observational	no	NA	no	NA	not reported
Wellard-Cole et al. (2019)	Australia	1	1	observational data from larger intervention study	no	NA	no	NA	voucher
Wharton et al. (2014)	USA	1	2	intervention	no	NA	no	NA	not reported
Wijayatunga et al. (2019)	USA	1	1	observational	no	NA	no	NA	not reported
Wouters et al. (2016)	the Netherlands	1	1	observational	no	NA	yes	Snacks	feedback, raffle
Wouters, Jacobs, et al. (2018b)	the Netherlands	1	1	observational	no	NA	yes	snacks	raffle
Wouters, Jacobs, et al. (2018a)	the Netherlands	1	1	observational	no	NA	yes	snacks	feedback, raffle
Wouters, Thewissen, et al. (2018)	the Netherlands	1	1	observational	no	NA	yes	Snacks	raffle
Yamaguchi et al. (2019)	Japan	1	1	observational	no	NA	no	NA	not reported
Ye et al. (2016)	USA	1	1	observational	no	NA	no	NA	not reported
Zia et al. (2016)	USA	1	1	observational	no	NA	no	NA	not reported
Ziesemer et al. (2020)	Germany	3							
		Study 1	1	observational	no	NA	no	NA	course credit, raffle
		Study 2	2	observational	no	NA	no	NA	money, course credit
		Study 3	1	observational	no	NA	no	NA	money, course credit

Table 3. Characteristics of included smartphone-based dietary assessment tools.

Paper	Study no.	Group no.	N	Sampling scheme	Name of tool	Operating system	Commercial app	Name of commercial app	Features to collect food intake data						Features to increase completeness of data		
									Photo-based assessment	Food database	Classification system	Free-text description	Assessment of serving or portion sizes	Other features	Related recordings	Skipped meals	Review
Aizawa et al. (2014)	1	1	18	event-contingent	FoodLog	NA	no	NA	yes	yes	no	no	yes	no	no	no	no
Ali et al. (2017)	1	1	54	event-contingent	NA	Android, iOS	no	NA	no	yes	no	no	yes	no	no	no	no
Ambrosini et al. (2018)	1	1	50	event-contingent	Research Food Diary	iOS	yes	Australian Calorie Counter - Easy Diet Diary	no	yes	no	no	yes	no	no	no	no
Antonio et al. (2018)	1	1	24	event-contingent	MyFitnessPal	NA	yes	MyFitnessPal	no	yes	no	no	yes	no	no	no	yes
Ashman et al. (2016)	1	1	26	event-contingent	NA	NA	yes	Evernote app	yes	no	no	yes	no	no	no	no	NA
Ashman et al. (2017)	1	1	26	event-contingent	DietBytes	NA	yes	Evernote	yes	no	no	yes	no	no	no	no	no
Béjar (2017)	1	1	187	other	e-12HR	Android	no	NA	no	no	yes	no	yes	no	no	no	no
Béjar and Vázquez-Limón (2017)	1	1	119	other	e-EPIDEMIOLOGY	Android	no	NA	no	no	yes	no	yes	no	no	no	no
Béjar et al. (2018)	1	1	87	mixed	e-12HR	Android	no	NA	no	no	yes	no	yes	no	no	no	no
Béjar et al. (2019)	1	1	203	mixed	e-12HR	Android	no	NA	no	no	yes	no	yes	no	no	no	no
Biel et al. (2018)	1	1	122	mixed	NA	Android, iOS	no	NA	yes	no	yes	no	no	yes	yes	no	no

Boh, Lemmens, et al. (2016)	1	1	100	mixed	NA	iOS	NA	NA	yes	no	yes	no	no	no	no	no	no
Boh, Jansen, et al. (2016)	1	1	134	mixed	NA	NA	NA	NA	yes	no	yes	no	no	no	no	no	no
Bucher Della Torre et al. (2017)	1	1	18	event-contingent	e-CA	iOS	no	NA	no	yes	no	no	yes	no	no	no	no
Butscher et al. (2016)	1	1	35	event-contingent	SmartAct toolbox	Android	no	NA	yes	yes	no	no	no	no	no	no	no
Carter et al. (2013)	1	1	50	other	MyMealMate	Android	no	NA	yes	yes	no	no	yes	no	yes	no	yes
Chaudhry et al. (2016)	1	1	8	event-contingent	DIMA-P	NA	no	NA	yes	yes	yes	no	yes	no	no	no	no
Chen et al. (2017)	1	1	28	event-contingent	NA	Android	no	NA	yes	no	no	yes	no	no	no	no	no
Chen et al. (2019)	1	1	47	event-contingent	MyFitnessPal	Android, iOS	yes	MyFitnessPal	no	yes	no	yes	yes	no	no	no	yes
Chmurzynska et al. (2018)	1	1	62	signal-contingent	NA	NA	no	NA	no	no	yes	no	no	no	no	no	no
Chun et al. (2018)	1	1	17	other	NA	Android	no	NA	no	no	no	yes	no	yes	no	no	no
Chung et al. (2019)	1	1	39	event-contingent	Foodprint	NA	no	NA	yes	no	no	yes	no	no	no	no	yes
Cordeiro et al. (2015)	1	1	27	event-contingent	DECAF Food Journal	NA	no	NA	yes	no	no	yes	no	no	no	no	no
Desai et al. (2019)	1	1	10	event-contingent	Glucoracle	NA	NA	NA	yes	no	no	yes	yes	no	no	no	no
Elliston, Ferguson, Schüz, et al. (2017)	1	1	51	mixed	HBART	Android	no	NA	no	no	yes	no	no	no	yes	no	no
Elliston, Ferguson and Schüz (2017)	1	1	61	mixed	HBART	Android	no	NA	no	no	yes	no	yes	yes	no	no	no
Elliston et al. (2019)	1	1	72	mixed	HBART	Android	NA	NA	no	no	yes	no	no	yes	no	no	no
Elliston et al. (2020)	1	1	94	mixed	HBART	Android	no	NA	no	no	yes	no	no	no	yes	no	no
Falkenberg et al. (2020)	1	1	36	event-contingent	MealLogger Pro	NA	yes	MealLogger Pro	yes	no	no	yes	no	no	no	no	no
Franja et al. (2020)	1	1	74	mixed	HBART	Android	no	NA	yes	no	yes	no	no	yes	yes	no	no
Fuchs et al. (2019)	1	1	28	event-contingent	NA	Android, iOS	yes	MS Xamarin	no	yes	yes	no	yes	no	no	no	no

Gatica-Perez et al. (2019)	1	1	122	event-contingent	Bites'n'bits	Android, iOS	no	NA	yes	no	no	no	no	no	yes	no	no
Gill and Panda (2015)	1	1	NA	mixed	Salk Metabolic App	iOS	no	NA	yes	no	no	yes	yes	no	no	no	no
	2	1	8	mixed	Salk Metabolic App	iOS	no	NA	yes	no	no	yes	yes	no	no	no	yes
Godfrey (2017)	1	1	16	event-contingent	NA	Android	yes	movisensXS	yes	no	no	no	no	no	yes	no	no
Groat et al. (2018)	1	1	14	event-contingent	iDECIDE	Android, iOS	no	NA	yes	yes	no	no	yes	no	no	no	yes
Hendrie et al. (2019)	1	1	283	mixed	VegEze	iOS	no	NA	no	no	yes	no	yes	no	no	no	no
Hezarjaribi et al. (2019)	1	1	13	mixed	EZNutriPal	Android	no	NA	no	no	no	yes	no	no	no	no	no
Hongu et al. (2015)	1	1	45	event-contingent	Recaller app	Android	no	NA	yes	no	no	no	no	no	no	no	no
Hsu et al. (2014)	1	1	1	NA	HealthMan	iOS	no	NA	no	no	no	no	yes	yes	no	no	yes
Jung (2017)	1	1	19	event-contingent	FIT (Food Intake Logger)	Android	no	NA	no	no	yes	no	no	no	no	no	no
Jung et al. (2017)	1	1	6	event-contingent	FRADA	NA	no	NA	yes	no	no	no	no	no	no	no	no
Jung et al. (2020)	1	1	1027	event-contingent	EaT	Android, iOS	no	NA	no	yes	no	yes	yes	no	no	no	yes
Karway et al. (2020)	1	1	35	NA	NA	NA	no	NA	yes	no	no	yes	no	no	yes	no	no
Kato-Lin et al. (2015)	1	1	48	event-contingent	NA	Android	no	NA	yes	no	yes	yes	yes	no	no	no	no
		2	49	event-contingent	NA	Android	no	NA	yes	no	yes	yes	yes	no	no	no	yes
		3	50	event-contingent	NA	Android	no	NA	yes	no	yes	yes	yes	no	no	no	yes
		4	45	event-contingent	NA	Android	no	NA	yes	no	yes	yes	yes	no	no	no	no
Keeney et al. (2012)	1	1	2	event-contingent	Meal Snap app	iOS	no	NA	yes	no	no	no	no	no	no	no	yes
Kong et al. (2016)	1	1	120	event-contingent	NA	NA	yes	pictures submitted via WeChat	yes	no	no	no	no	no	no	no	no
König and Renner (2018)	1	1	108	event-contingent	NA	Android	yes	movisensXS	yes	no	no	yes	no	no	no	no	no

König and Renner (2019)	1	1	80	event-contingent	none reported	Android	yes	movisensXS	yes	no	no	yes	no	no	yes	yes	no
Ladzynski et al. (2018)	1	1	30	event-contingent	VoiceDiab	Android	no	NA	no	no	no	yes	yes	no	no	no	yes
Leipold et al. (2018)	1	1	14	mixed	Nutrilize	Android	no	NA	no	yes	no	no	yes	no	no	no	yes
Lim et al. (2017)	1	1	6	event-contingent	Nibble	NA	no	NA	yes	yes	no	no	no	no	no	no	yes
Lozano-Lozano et al. (2018)	1	1	20	other	BENECA mHealth system	Android	no	NA	no	yes	no	no	yes	no	no	no	no
Maher et al. (2020)	1	1	50	signal-contingent	movisensXS	Android	yes	movisensXS	no	no	yes	no	no	no	no	no	no
Martin et al. (2012)	1	1	40	event-contingent	Remote Food Photography Method	NA	no	NA	yes	no	no	no	no	no	no	no	no
	2	1	50	event-contingent	Remote Food Photography Method	NA	no	NA	yes	no	no	no	no	no	no	no	no
Mattila et al. (2008)	1	1	27	event-contingent	Wellness Diary	Symbian OS	no	NA	no	no	yes	yes	no	no	yes	no	yes
Mattila et al. (2010)	1	1	27	event-contingent	Wellness Diary	Symbian OS	no	NA	no	no	yes	yes	no	no	no	no	no
McCarroll et al. (2015)	1	1	NA	NA	LoseIt!	NA	yes	LoseIt!	no	yes	no	yes	yes	no	NA	no	yes
McHill et al. (2017)	1	1	110	event-contingent	MealLogger	NA	yes	MealLogger	yes	no	no	yes	yes	no	no	no	no
McHill et al. (2019)	1	1	106	event-contingent	MealLogger	Android, iOS	yes	MealLogger	yes	no	no	yes	no	no	no	no	no
Mescoloto et al. (2017)	1	1	40	event-contingent	Nutrabem	NA	yes	Nutrabem	no	no	no	yes	yes	no	no	no	no
Meule et al. (2019)	1	1	105	signal-contingent	NA	NA	yes	PsyDiary	no	no	no	no	no	yes	no	no	no
Mirtchouk et al. (2017)	1	1	11	event-contingent	NA	Android	NA	NA	no	no	no	yes	no	no	no	no	no
Most et al. (2018)	1	1	23	event-contingent	SmartIntake	iOS	no	NA	yes	no	no	yes	no	no	no	no	no
Most et al. (2019)	1	1	56	event-contingent	SmartIntake	NA	NA	unclear	yes	no	no	no	no	no	no	no	no
Mumma et al. (2016)	1	1	8	mixed	Vegethon	iOS	no	NA	no	no	yes	no	yes	no	no	no	yes

Nandy et al. (2019)	1	1	155	signal-contingent	NA	NA	NA	NA	no	no	yes	no	yes	no	no	no	no
O'Connor et al. (2019)	1	1	65	signal-contingent	NA	Android	yes	movisensXS	no	no	yes	no	no	no	no	no	no
Panza (2018)	1	1	55	mixed	Lifedata	Android, iOS	yes	LifeData	no	no	no	yes	yes	no	no	no	no
Parr et al. (2018)	1	1	8	event-contingent	Easy Diet Diary	iOS	no	NA	no	yes	no	yes	yes	no	no	no	no
Pellegrini et al. (2018)	1	1	32	event-contingent	ENGAGED app	NA	no	NA	no	yes	no	no	yes	no	no	no	yes
Pendergast et al. (2017)	1	1	56	event-contingent	FoodNow	Android, iOS	no	NA	yes	no	no	yes	yes	no	no	no	no
Pentikäinen et al. (2019)	1	1	37	event-contingent	Button	Android	no	NA	no	no	yes	no	no	no	no	no	yes
		2	37	event-contingent	Button	Android	no	NA	no	no	yes	no	no	no	no	no	yes
Perez et al. (2015)	1	1	2	signal-contingent	NA	Android	no	NA	yes	no	yes	no	no	no	no	no	yes
Poelman et al. (2020)	1	1	140	event-contingent	FoodTrack Smartphone App	Android, iOS	no	NA	no	yes	no	no	yes	no	no	no	no
Rabbi, Pfammatter, et al. (2015)	1	1	17	NA	MyBehavior	Android	no	NA	yes	yes	no	no	yes	yes	yes	no	no
Rabbi, Aung, et al. (2015)	1	1	16	event-contingent	My Behavior 2.0	Android	no	NA	yes	no	no	no	no	no	no	no	no
	2	1	7	event-contingent	My Behavior 2.0	Android	no	NA	yes	no	no	no	no	no	no	no	no
Rangan et al. (2015)	1	1	80	event-contingent	e-DIA	Android, iOS	no	NA	no	yes	no	yes	yes	no	no	no	no
Rangan et al. (2016)	1	1	80	event-contingent	e-DIA	Android, iOS	no	NA	no	yes	no	yes	yes	no	no	no	no
Raynor et al. (2019)	1	1	60	event-contingent	MyFitnessPal	NA	yes	MyFitnessPal	no	yes	no	no	yes	no	no	no	yes
Recio-Rodriguez et al. (2019)	1	1	362	NA	EVIDENT app	NA	no	NA	no	yes	no	no	yes	no	no	no	no
Regan et al. (2020)	1	1	9	mixed	FoodFoto	iOS	no	NA	yes	no	no	yes	no	no	no	no	no
Richard et al. (2017)	1	1	61	signal-contingent	NA	NA	NA	NA	no	no	no	yes	yes	no	no	no	no

Richard et al. (2019)	1	1	60	signal-contingent	PsyDiary	Android	no	NA	no	no	no	yes	no	no	no	no	no
Robinson et al. (2013)	1	1	12	event-contingent	NA	iOS	no	NA	yes	no	no	no	no	no	no	no	yes
Roefs et al. (2019)	1	1	100	mixed	NA	iOS	NA	NA	yes	no	yes	no	no	no	no	no	no
Roy et al. (2017)	1	1	103	event-contingent	e-DIA	NA	no	NA	no	yes	no	no	yes	no	no	no	yes
Schüz, Schüz, et al. (2015)	1	1	53	mixed	HBART	Android	no	NA	no	no	yes	no	no	no	yes	no	no
Schüz, Bower, et al. (2015)	1	1	53	mixed	HBART	Android	no	NA	no	no	yes	no	no	no	yes	no	no
Schüz et al. (2017)	1	1	112	mixed	HBART	Android	no	NA	no	no	yes	no	no	no	no	no	no
Schüz et al. (2018)	1	1	61	mixed	HBART	Android	no	NA	no	no	yes	no	no	no	no	no	no
Seitzinger et al. (2019)	1	1	96	event-contingent	Ethica	Android	no	NA	yes	no	no	yes	no	no	no	no	no
Seto et al. (2014)	1	1	12	event-contingent	CalFit	Android	no	NA	yes	no	no	yes	yes	no	no	no	no
Seto et al. (2016)	1	1	12	mixed	CalFit Chi and Dong	Android	no	NA	yes	no	no	yes	yes	no	no	no	no
Simpson et al. (2017)	1	1	17	event-contingent	MealLogger	Android, iOS	yes	MealLogger	yes	no	no	no	no	no	no	no	NA
Skinner (2019)	1	1	94	mixed	LifeData application	Android, iOS	yes	LifeData	no	no	no	no	yes	no	no	no	no
Spanakis et al. (2015)	1	1	100	mixed	NA	iOS	no	NA	yes	no	yes	no	no	no	no	no	no
Spring et al. (2018)	1	1	212	event-contingent	NA	NA	NA	NA	no	yes	no	no	yes	no	no	no	yes
Stein and Brooks (2017)	1	1	70	event-contingent	Lark HCAI	Android, iOS	yes	Lark HCAI	no	no	no	yes	no	no	no	no	yes
Teixeira et al. (2018)	1	1	30	event-contingent	MyFitnessPal	NA	yes	MyFitnessPal	no	yes	no	no	yes	no	no	no	yes
Tejpal et al. (2019)	1	1	52	NA	NA	Android	no	NA	no	yes	no	no	yes	no	no	no	no
Terzimehić et al. (2016)	1	1	NA	event-contingent	NA	Android	no	NA	no	yes	no	no	yes	no	no	no	yes
Villinger et al. (2020)	1	1	73	event-contingent	SMARTFOOD	Android	no	NA	yes	yes	no	no	yes	no	yes	no	yes
Wahl et al. (2017)	1	1	38	event-contingent	NA	Android	yes	movisensXS	yes	no	no	yes	no	no	no	no	no
Waki et al. (2015)	1	1	22	NA	DialBetics	NA	no	NA	yes	no	no	no	no	no	no	no	no

	2	1	5	NA	DialBetics with FoodLog	Android	no	NA	yes	no	no	no	no	no	no	no	no
Wang et al. (2018)	1	1	45	event-contingent	TADA mobile application	Android, iOS	no	NA	yes	yes	no	no	no	no	no	no	yes
Wellard-Cole et al. (2018)	1	1	NA	event-contingent	EaT app	NA	no	NA	no	yes	no	yes	yes	no	yes	no	no
Wellard-Cole et al. (2019)	1	1	189	event-contingent	EaT app	Android, iOS	no	NA	no	yes	no	no	yes	no	no	no	no
Wharton et al. (2014)	1	1	19	event-contingent	Lose It!	iOS	yes	Lose it!	no	yes	no	no	yes	no	yes	no	yes
	1	2	13	event-contingent	NA	no restriction	NA	NA	no	no	no	yes	no	no	yes	no	no
Wijayatunga et al. (2019)	1	1	17	event-contingent	SmartIntake	iOS	no	NA	yes	no	no	yes	yes	no	no	no	no
Wouters et al. (2016)	1	1	269	mixed	Snackimpuls Smartphone App	Android	no	NA	no	yes	no	yes	yes	no	no	no	no
Wouters, Jacobs, et al. (2018b)	1	1	46	signal-contingent	Snackimpuls Smartphone App	Android	no	NA	no	yes	no	yes	yes	no	no	no	no
Wouters, Jacobs, et al. (2018a)	1	1	269	mixed	Snackimpuls Smartphone App	Android	no	NA	no	yes	no	yes	yes	no	no	no	no
Wouters, Thewissen, et al. (2018)	1	1	269	signal-contingent	Snackimpuls Smartphone App	Android	no	NA	no	yes	no	yes	yes	no	no	no	no
Yamaguchi et al. (2019)	1	1	522	NA	Glucote	iOS	yes	Apple ResearchKit	yes	yes	no	no	yes	no	no	no	yes
Ye et al. (2016)	1	1	7	signal-contingent	NA	Android	no	NA	yes	no	no	yes	no	no	no	no	no
Zia et al. (2016)	1	1	11	event-contingent	NA	iOS	yes	Apple Xcode 4.0	no	no	no	yes	yes	yes	no	no	yes
Ziesemer et al. (2020)	1	1	38	event-contingent	NA	Android	yes	movisensXS	yes	no	no	yes	no	no	no	no	no
	2	1	18	event-contingent	SMARTFOOD	Android	no	NA	yes	no	no	yes	no	no	yes	no	no
	2	2	17	event-contingent	SMARTFOOD	Android	no	NA	yes	no	no	yes	no	no	no	no	no
	3	1	110	event-contingent	NA	Android	yes	movisensXS	yes	no	no	yes	no	no	yes	yes	no

Table 4. Summary of common characteristics of the features for assessing dietary data, highlighting the most important aspects for reporting smartphone-based dietary assessment tools.

	Photo-based assessment	Food database	Classification system	Free-text description	Assessment of serving or portion sizes
Assessing what is consumed	Yes; level of detail depends on data processing	Yes; level of detail depends on the database, but usually more detailed than classification system	Yes; level of detail depends on the provided options, but usually less detailed than food database	Yes; level of detail depends on instructions and may vary between participants.	No
Assessing how much is consumed	Yes; level of detail depends on data processing	No	No	Yes; level of detail depends on instructions and may vary between participants.	Yes; usually in grams or common household measures (e.g., spoonfuls, cups)
Summary of common assessment procedures	<p>Procedure and recorded materials differ between tools. Most tools use photos, while a small number of tools uses videos instead.</p> <ul style="list-style-type: none"> • Use of photos: <ul style="list-style-type: none"> ○ Participants usually take a photo before eating; many studies also include photo of leftovers to allow for the estimation of amount consumed (vs. amount served). Researchers may provide instructions on distance and/ or angle. ○ A fiducial marker may be included as a size/ colour reference. • Use of videos: <ul style="list-style-type: none"> ○ Short video clips with voice annotation may be recorded. 	Participants search for the food items and select the most fitting entry. Usually, several entries need to be selected per record.	Participants are presented with a list of options or visual presentations (e.g., icons, photos) and check all that apply.	Participants describe their food/ drinks in an open text field or using voice recording. Depending on the instructions, participants may report information on what and how much they consumed, cooking methods, brands, restaurants etc.	Participants estimate portion sizes in grams of using common household measures and enter them in a text field. They may be provided with an estimation aid (e.g., pictures). Few studies asked participants to estimate the energy or macronutrient content.

Summary of common data processing procedures	<p>Data processing necessary. Degree of automation varies between tool.</p> <p>Manual image analysis:</p> <ul style="list-style-type: none"> Usually performed by trained raters (e.g., members of research team, trained dieticians) with the help of a coding manual/ reference pictures/ professional software with food databases. <p>Semi-automated image analysis:</p> <ul style="list-style-type: none"> Image-analysis algorithm is used to provide a (range of) estimates for quantity and/ or type of food. <p>Automated image analysis</p> <ul style="list-style-type: none"> Using algorithms (e.g., artificial intelligence) 	Output from app can be directly used.	Output from app can be directly used.	<p>Data processing necessary. Degree of automation varies between tool.</p> <p>Manual analysis:</p> <ul style="list-style-type: none"> Manual transcription/ re-organisation of recorded data Usually performed by trained raters (e.g., members of research team, trained dieticians) with the help of a coding manual/ professional software with food databases <p>Semi-automated analysis:</p> <ul style="list-style-type: none"> Transcription and identification of food items using an algorithm. Further analysis performed by trained raters (e.g., members of research team, trained dieticians) with the help of a coding manual/ professional software with food databases 	Output from app can be directly used.
Useful combination with other features	Free-text descriptions may provide useful information for coding the photos.	Often combined with provision of portion or serving sizes through the participant, which may be linked to nutritional information stored in the database.			Often combined with food databases to calculate energy, macro- or micronutrient consumption based on nutritional information stored in the database.
Additional considerations for reporting	Provide as much detail as possible on instructions and training that participants and raters received. Provide as detailed information as possible on all information that was extracted from the photos. If applicable, provide indicators for accuracy,	Provide information on which database was used, including the version. Provide a description of the level of detail of the	Provide a full list of options to ensure replicability.	Provide as much detail as possible on instructions and training that participants and raters received. Provide as detailed information as possible on all information that was extracted from the descriptions. If	Provide as much detail as possible on the quantification measures provided to participants (e.g., which were used; were participants able to

especially if multiple raters were involved. If applicable, provide detailed description of/ reference to algorithm used for analysis and indicators for its accuracy.

database (e.g., whether cooking methods or brands were differentiated) and number of entries.

applicable, provide indicators for accuracy, especially if multiple raters were involved. If applicable, provide detailed description of/ reference to algorithm used for analysis and indicators for its accuracy.

choose between different measures; how were different measures such as grams and cups converted). Provide as much detail as possible on instructions and training that participants received.

Table 5. Summary of common characteristics of the features for ensuring completeness of the data, highlighting the most important aspects for reporting smartphone-based dietary assessment tools.

	Opportunity to review and amend	Add belated recordings	Report skipped meals
Used to ensure completeness and accuracy of provided records	Yes	No	No
Used to ensure that as many records as possible are provided	No	Yes	Yes
Common implementations	<ul style="list-style-type: none"> Some apps allow participants to review the record immediately after it has been saved. This may be used if the app processes the data (e.g., automated analysis of image content) to allow the participant to accept or reject suggestions. Other apps allow participants to review entries for an extended period of time (e.g., for this day, for the duration of the study), however, this may serve as a feedback intervention and thus impact behaviour. 	<p>Initiation of a belated recording differed between tools:</p> <ul style="list-style-type: none"> Participants may initiate a belated recording themselves through the tool. An evening report may ask participants whether they forgot to record any foods that they consumed. <p>When completing a belated recording, participants may be asked to provide information on when the food was consumed in addition to other information that is also assessed during in-the-moment recordings. Typically, belated recordings had to be provided by the end of the day.</p>	<p>Skipped meals can be indicated in different ways:</p> <ul style="list-style-type: none"> By pressing a button in the tool In an evening report
Additional considerations for reporting	Report what and for how long participants were able to review and amend entries	Provide information on how, when and until when belated recordings could be initiated, and whether the information recorded differed from the usual recording.	Provide information on how, when and until when skipped meals could be recorded and whether (and if so, which) information was additionally recorded.

Appendix D

Appendix D can be downloaded from <https://osf.io/xg8s6/>.