Automation of Data Collection Techniques for Recording Food Intake: a Review of Publicly Available and Well-Adopted Diet Apps

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***Abstract* — There has been a proliferation in the development of diet-related smartphone applications (mHealth) that support diet monitoring and can provide health-beneficial interventions. With these developments, the collection of accurate dietary consumption data is becoming an important field in mHealth, as less automated data collection techniques (DCT's) are often associated with underreporting, ineffective or non-tailored interventions, and self-selection of motivated users and/or high attrition rates. Interventions that incorporate more automated or passive DCT's have been linked with greater potential for user adoption and engagement, it remains unclear however what DCT's exist and to what extent mHealth apps incorporate such techniques. As such, the purpose of this study is to investigate the presence of DCTs in well-adopted dietary apps and provide an overview of existing and emerging approaches.**

Keywords—uHealth, mHealth, data collection, nutrition, diet

I. INTRODUCTION

Lifestyle behaviours such as high calorific diets are mitigatable risk factors associated with many diet-related non-communicable diseases (NCDs). These account for 63 per cent of deaths worldwide [1], [2]. To date, many intervention programs targeting dietary changes have had only modest effects and their long-term effectiveness is not well established [3], [4]. Thus, public health researchers have begun to examine novel approaches to deliver behaviour change interventions. Mobile (mHealth) and ubiquitous health applications (uHealth) are a growing field in the prevention and management of NCDs and hold potential to deliver scalable, tailored health-related behaviour change interventions [5]. Mobile phone ownership has reached saturation in many industrial and developing countries with smartphone ownership rates of 90% and 70% respectively. As such diet-related mHealth hence promises inclusive and scalable means for health behavior change [6].

Despite the recent proliferation of apps to promote positive lifestyle change, there is a dearth of research evidence regarding their long-term effectiveness. While it has been acknowledged that novel technologies increase the likelihood of supporting behaviour change [7], it appears that current DCT approaches prove inadequate to fully complement mHealth interventions. For example, Mateo and colleagues [8] suggest that diet-related apps must become engaging in more relevant ways during usage and less effort-intensive. Further research has associated less automated DCTs with user attrition [9]–[12] as well as memory and recognition biases that reduce intervention effectivity of mHealth apps [12], [13]. In turn, further potentially discouraging the adoption of inexpensive diet-related health interventions.

While studies have been conducted to determine the extent to which data collection techniques have been applied to app development (e.g. [14]), none have quantified the extent to which specific DCT's are included. Moreover, we found that the few app reviews that exist focus on a selected subgroup of DCT's. As such we lack a comprehensive overview of DCT's available today. Another limitation we see in this nascent field is that the aforementioned reviews - if not conceptual - have focused exclusively on apps that are not publicly available. However, without the use of qualitative or quantitative analysis of publicly available apps, on which many researchers, users and application developers rely on, we lack validation of DCT's that are widely in use.

To provide more insight regarding these gaps, we first developed an overview of existing DCT's, discussed in the literature. In a next step this framework allowed us to conduct a systematic determination of the presence/absence of DCT's in a set of publicly available and well-adopted diet apps from the German speaking Google App Store, as the dominant mobile operating system in the country. We specifically selected Germany, as its 'aging society' is representative for the future of many developed countries, displaying high levels of NCD's as well as high adoption of mobile devices and applications. We discuss the implications for theory and clinical practice, and identify research-practice gaps that hopefully stimulate the development of more sophisticated diet apps.

II. DATA COLLECTION TECHNIQUES

With the proliferation of improved technological means, the collection of accurate dietary consumption data is becoming an important field in mHealth as well as related fields such as nutritional epidemiology [15]. Accurate intake data allows to establish relationships between nutrition and health state. Traditionally implemented methods of food diaries usually involve the manual text entry of identifier and quantified amount of the consumed foods [16]. Such methods bear multiple issues most notably related to convenience and accuracy. The former involves a high burden that is placed upon respondents to record dietary information and to do so continuously, multiple times per day [10]. The latter involves memory biases leading to underreporting of dietary intake [13]. Thus, improvements in form of more automized data collection methods that address these issues would be beneficial for research participants and researchers alike.

The rapid and ubiquitous uptake of smartphones and connected technologies that could enable automated data collection techniques for diet monitoring have sparked interest from researchers in regard to improved convenience and accuracy for users [17], [18]. In fact, a variety of alternative DTC's exist in order to capture information on nutritional intake within mHealth systems, ranging from manual text-entry logging of each consumed food item to wearable sensors that detect diet-related activity automatically, albeit with varying levels of automation as well as comfort, accuracy, advantages and challenges. Three reviews have compared diet applications by DTC. We build on these studies, by compiling their DCT's and reviewing recent DCT's discussed in the literature to provide a more comprehensive overview. In doing so, we grouped the different techniques by automation degree (see [14]).

A. Manual DCTs

Entering. The *Entry* technqiue on mHealth apps resemble traditional handwritten self-reports (e.g. 24h food recall diaries). Systems relying on manual entry require the user to enter individual food items and the amount consumed through manual text input [19], [20]. While manual entries require little user education, text-based entry methods also heavily rely on conscious record-keeping, recall and memory. These characteristics have been associated with underreporting and user attrition [9]–[12]. Hence, some mHealth apps have introduced supporting functions. Some examples involve auto-completion of text input, bookmarking of preferred items, search functionality within food item databases, all of which reduce manual effort to search for food items [20], [21].

Selecting. For certain mHealth apps, relevant food items might be compiled into food record checklists [22] or food frequency questionnaires [23] or recently used food items. These suggest a finite number of food items to the user, from which usually multiple consumed items can be selected within a single click or tap. The selection from pre-configured or configurable combination of food items represents another example of a selection-based DCT. Here the user for example creates or selects a complete recipe or meal that was consumed [18]. The *Select* technique hence reduces search costs, offering less effort-intensive food logging, as the user only selects from a limited number of relevant food items or meals to reliable self-report dietary intake [24]–[26]. The downsides associated with selection methods occur when predefined items differ from actually consumed items, such that recorded diaries are inaccurate or require further manual entry.

B. Semi-automatic DCT

Scanning. Some diet-related mHealth apps feature barcode scanning functionality, through which a user can conveniently identify a consumed product by scanning its identifier on packaged goods [17], [20]. Such identifiers in form of Global Trade Item Number (GTIN) or Universal Product Code (UPC) [27] unfortunately however may not always be available. For example, not all food items contain barcodes (e.g. unpackaged fruits and vegetables or cooked dishes), and users cannot rely on barcodes when eating out. Moreover, incomplete food composition databases and insufficient data quality, which can substantially falsify user's dietary intake[1]. Still, when correctly identified, the *scan* technique represents a powerful and unambiguous data collection technique [17]. Moreover, some apps have begun to reduce the number of necessary scans, by integrating Object Character Recognition (OCR) to interpret printed supermarket receipts and query relevant data for multiple products in one scan process [18], [28].

TABLE I.

#	Data Collection Techniques and Input Methods		
	DCT	***Input Method (DCT ID)***	***Automation Degree***
1	ENTER	Text entry per food item (1.1), supported text entry (1.2)	Manual
2	SELECT	Selection from item shortlist (2.1), select pre-/configurable meals (2.2)	Manual
3	SCAN	Scanning a product barcode (3.1), scanning a printed receipt (3.2)	Semi-Automatic
4	RECORD	Voice entry actively logged (4.1), voice entry through prompts (4.2)	Semi-Automatic
5	CAPTURE	Capturing food items (5.1), capturing food items and quantities (5.2)	Semi-Automatic
6	RECEIVE	Automatic receipt feed	Automatic
7	SENSE	Automatic sync of sensors detecting eating activity	Automatic

Recording. With the growing popularity of smartphone embedded voice assistants such as Apple Siri, users increasingly engage with applications via voice. As voice-to-text transcription eases the effort involved in logging food items voice recordings and language processing appear promising for nutritional intake logging [20]. Users then either need to actively enter the voice recording, or could be prompted to record food items or meals when eating sounds are detected [5], [18], [19].

Capturing. With the recent progresses of visual computing [29], automatically deriving a meal's characteristics and quantity from a picture or video has become technically feasible [5], [18], [19] and has been integrated in diet-related applications [21], [30]. Primary elements of visual computing-based intake assessments are the segmentation and quantification of meal components [5]. Capturing includes input methods of food item recognition, as well as food item and quantity recognition.

C. Automatic DCTs

Receiving. Digital receipts from payment or loyalty cards of retailers present a rich, instantly up-to-date data source that allows for automatic, low-cost monitoring of grocery purchases [18], [31]. In some countries, over 80 percent of revenue of a single retailer can be attributed to individual loyalty accounts [32]. This data can prove valuable for diet

[1] In this regard, the EU Food Information Regulation (EU-1169/2011 2014) on the provision of food information online is paving the way for publicly accessible product databases covering multiple retailers and brands, supporting barcode scanning as a data collection technique for dietary mHealth applications.

monitoring, when combined with food composition product data bases [31], [33], [34]. When collected purchasing data is provided automatically, such data feeds represent a completely effortless data collection technique. Yet, its accuracy depends on estimation models that can account for circumstances such as household level data or frequency of restaurant visits. These considerations have led some researchers to consider a combination and calibration of digital receipts with other accurate data collection techniques, such as manual entry-based food diaries [18].

Sensing. Due to advances in the miniaturization of devices, detection of diet-related activities is increasingly feasible through an ever smaller and ubiquitously available range of wearables or non-wearable sensors [5], [19]. These sensors are considered a fully automatic data collection technique once the user can forgo syncing his or her data manually. Instead, the synchronization of the mHealth system and sensor happens automatically [35]. These devices amongst other things can monitor arm gestures, swallowing or chewing activity through means of electroglottography (EGG) or electromyography (EMG), piezoelectric charge, accelerometers or acoustic microphones [5], [19]. Wearables include smartwatches or camera-enhanced smart-glasses [36]. Non-wearables include pressure-sensitive tablecloths [19], sensor-based spatulas and plates [37] or beverage cups [38]. Albeit not yet observed, smart home systems such as Google Home, Amazon Echo could also deem helpful when logging diet, as the home system could passively trigger a prompt when breakfast or dinner activity has been detected. Such sensors however usually only detect a subset of eating-related activities, therefore it is recommended to combine and calibrate sensor-based activity detection with other data collection techniques [19].

III. METHODS

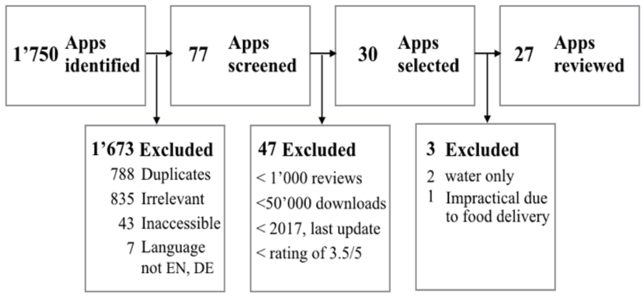
The assessment of data collection techniques in popular diet apps was undertaken by four independent raters. The rater panel consisted of two dieticians familiar with mHealth applications and two IS researchers, focused on health behavior change. The study was conducted in accordance to ethical standards.

A. *App Sampling*

Our systematic sampling approach follows the four-phase PRISMA process, illustrated in Fig. 1 [39]. In a first step, we imitated a layman's app search. To this end, we entered relevant German equivalents of the following search terms: "diet", "diet app", "nutrition", "food", and combinations "healthy diet", "food coach" and "nutrition coach" into the Google Play store. We decided to limit our search to this store, as Android represents the dominant mobile operating system in this context (market share < 65% [40]).

The sampling was conducted in Q4/2017, where we identified 1'750 apps, based on the app store's search output. A pre-screening led to the exclusion of 1'673 apps, which consisted mostly of duplicates appearing across search terms or nutrition-irrelevant apps (e.g. social media apps, calendars, games, learning apps). Next, we screened the resulting 77 apps. To ensure we would rate apps that are widely adopted, we excluded apps, if they had less than 1'000 reviews, less than 50'000 downloads, no up-to-date version, or a user rating lower than 3.5 out of 5, based on inclusion criteria used in previous mHealth app reviews (cf. [41]). This screening led to our total sample of 27 apps.

Fig. 1 PRISMA



B. *Measurement*

We collected an exhaustive list of alternative data collection techniques based on the recent app reviews [17], [20], [21] and technology review papers [5], [18], [19], see Table 1. We used this framework for the present evaluation. Each app was rated for inclusion of each of the seven data collection techniques. We refrained from formal statistical comparisons in terms of differences in number of DCT's between apps for two reasons. First, the aim of the study was to synthesize previous work on DCT's and to explore them in public and well-adopted diet apps. Second, given the number of apps assessed and the potential for differences in DCT's between apps, the number of comparisons needed would likely result in Type 1 errors (cf. [42]).

C. *Procedure*

For each app, descriptive information was retrieved regarding its popularity (i.e. frequency of downloads relative to other apps within the same category), average rating (i.e. average number of stars the app was rated ranging one to five), total ratings (i.e. number of users who downloaded the app and voluntarily rated it), total "hate it", "don't like it", "it's ok", "it's good", and "it's great" ratings (i.e. number of times the app was rated with one to five stars, respectively), customer reviews (i.e. number of times the app was reviewed) and price. Every app was evaluated by four independent raters between October 2017 and February 2018. The four raters separately tested all apps in detail to become familiar with the interfaces, menus, features, and functionality, and later independently user-tested. Prior to evaluation, all raters read the DCT's definitions carefully and had the opportunity to clarify and discuss the definitions. Before beginning a coding session raters read each DCT description carefully to ensure clear differentiation between techniques. After using each app, raters reviewed each of the menu functions to rate the presence or absence of DCT's according to the checklist. A dichotomous score of "0" absent or "1" present was applied for each of the 7 DCT's. Disagreements were resolved by consensus discussion.

D. Descriptive Statistical Analyses

All descriptive analyses were conducted using R: Frequencies and percentages of each of the 7 DCT's included in the 27 apps were calculated. Krippendorff's alpha was used to evaluate interrater reliability for each of the 7 DCT's. This statistic is appropriate because it can be used with any number of observers, sample sizes, and satisfies all criteria for a good measure of reliability [43].

IV. RESULTS

Out of the 27 mHealth diet apps reviewed, with the exception of one app all of the apps were available for both iOS and Android. Private companies or developers accounted for the development of all apps, and none of them were clinically validated. In the following we present the findings in regard to the prevalence of the different DCT's and their input methods among the sampled apps. Then we illustrate the automation degree of the sampled apps and end our analysis with a discussion on associated costs.

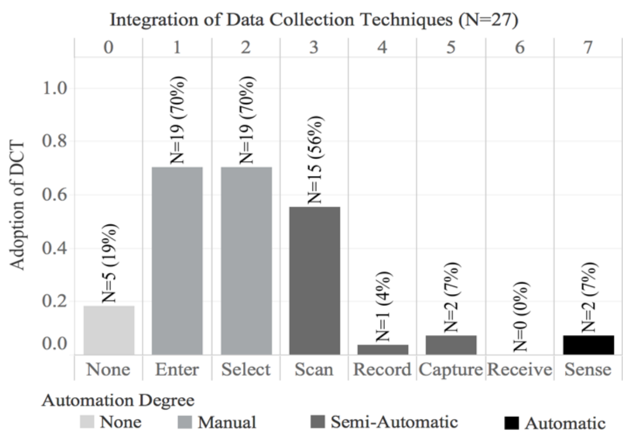
A. Prevalance of Data Collection Techniques in Sample

Overall, we found that out of the 27 most popular apps in the German speaking area five apps (20%) remained purely informative and as such did not aid the user in following a food intake dairy. Within the remaining 22 apps, manual DCT's were the most frequently implemented food logging technique. Many apps also included semi-automatic DCT's, especially in form of barcode scanning. Finally, we observed that automatic DCT's still remain the exception among implemented DCT's in popular mHealth diet related apps. We discuss the prevalence now by automation degree.

Manual DCT's. Manual Entering and Selection based techniques represented the most widely adopted data collection tech*niques (70%, 19/27), see Fig. 2*. Entering and Selecting appear to be the current standard for diet monitoring in mHealth. All of these apps relied on manual text-based entry methods (19/19), and most of them also offered supportive entry functions (17/19). This finding suggests, that app developers have recognized the utility of automating already in manual data collection techniques, most notably by means of auto-completion of text input and predictive text search options. In regard to selection mechanisms (70%, 19/27), almost all apps provided selection of pre-defined foods and meals (18/19), whereas only around half of them allowed users to select from pre-configured or configurable food item combinations or recipes (11/19). These findings suggest that developers acknowledge the need for more personalizable DTC means, especially since the selection of food item combinations can save redundant steps of reiterative text-based entries of multiple items that would otherwise require separate entries

Semi-automatic DCT's. A total of 14 apps made use of scanning-based DC input methods for diet monitoring (14/27, 52%). Interestingly, all of these apps relied on barcode scanning of single products (14/14), whereas none of the applications could scan and interpret printed grocery receipts via OCR (0/14). A reason for this finding may be that this method has only recently been implemented in end-user applications [18], [28]. Also, this circumstance may be further explained by the fact that retailers hardly provide public databases with food identifiers or publish aggregated data on food compositions. Surprisingly, capturing and recording hardly featured in any of the observed apps.

Fig. 2 Frequency Table of DCT's



Capturing featured among 2 apps (7%, 2/27), and required the user to either actively take and confirm images (2/2). None of these apps assessed image or video data automatically (0/2). Recording featured in one app only (4%). This app used actively triggered voice recording for dietary logging (1/1). It was not possible however to activate prompts for voice recording (0/1). The absence of both capturing and recording based techniques in the majority of the apps appears striking in so far that image recognition and voice-to-text transcriptions for other mobile applications and wearables are increasingly used and, in some cases, becoming common place for daily actions in smart home set-ups for example.

Automatic DCT's. Sensing belonged to the least common techniques applied among the observed apps. Despite its potential convenience for users, it only featured in two apps (7%, 2/27), in ways that directly related to dietary behavior. In one case, sensing required the user to actively sync the data periodically, in the other case the data syncing was automated from the glucose monitoring device (Samsung Health, Dexcom). However, it should be pointed out that automatically-synced sensing methods related to physical activity and health (e.g. steps, body temperature, calorie expenditure) were identified in 14 apps (52%, 14/27), yet are traditionally not considered primarily relevant data in diet monitoring studies. Moreover, none of the apps proposed the use of diet-related smart home devices. We attribute this status quo to the current low supply and adoption rates of such devices, and in turn the low number of interfaces that exist. Finally, none of the apps used receipt data from payment or loyalty card providers in our review. The absence of receipt-based methods appears sensible given the fact that digital receipt standards (e.g. based on loyalty card programs) remain nascent and are not necessarily available in electronically processable formats, yet.

TABLE II.

#	Overview of sampled Apps (N = 27)		
	*App**	*Category***	*Cost****
1	8fit Workout^{M}	1	30.00
2	Abnehmen ohne Diaet^{M}	1	3.50
3	barcoo QR^{F}	4	free
4	Calorie Counter & Diet Tracker^{M}	1	15.75
5	Coach by Cigna^{F}	6	free
6	CodeCheck^{M}	4	2.90
7	Eat Smarter^{F}	2	free
8	Fitbit^{F}	1	free
9	Fooducate^{M}	1	17.70
10	Kalorien^{M}	1	21.10
11	FDDB^{M}	1	free
12	MyFitnessPal^{M}	1	35.30
13	Life Balance^{M}	1	1.50
14	FatSecret^{F}	1	free
15	Kitchen Stories^{F}	2	free
16	KptnCook^{M}	2	16.00
17	Lifesum^{M}	1	28.25
18	Lose it!^{M}	1	9.45
19	Meine Diaet^{P}	1	14.15
20	My Diet Diary^{F}	1	free
21	Naehrwerte^{F}	4	free
22	Noom Coach^{M}	1	141.25
23	Runtasty^{M}	2	free
24	Samsung Health^{F}	1	free
25	Weight Watchers^{M}	1	51.00
26	WeightWar^{M}	1	14.75
27	Yazio^{M}	1	23.50

* App business model: ^{F} = Free, ^{M}= Freemium, ^{P}=Paid.
** Categories by Azar [47]: Diet Tracking (1), Health Cooking (2), Weight/ Anthropometric Tracking (3), Grocery Decision (4), Restaurant Decision (5), Other (6)
*** Costs as encountered by raters, est. per quarter, in USD

B. *Automation Degree of Sampled Apps*

In terms of automation degree, we were able to identify all three levels of automation (manual, semi-automatic, and automatic), however to different degrees (see Fig. 3). Nine apps (33%) did not rely on any form of automation and remained purely didactical or involved mostly manual DCT's. These apps were mainly informational and often contained recipes and information about diet-related health. In terms of semi-automation, 16 apps (59%) made use of semi-automatic DCT's, especially in form of barcode scanning. In almost all apps the latter was combined with manual DCT's. This finding suggests that app developers chose to combine DCT's to prevent lose of data, when one DCT's malfunctions for the user. For example, the user can enter a product, if a grocery item does not possess a barcode on its packaging. In terms of full automation, we identified only two apps that offered more automated DCT's (7%). The raters however noted that these were not yet fully developed, and accurate food logging was not possible without the use of additional semi-automatic or manual DCT's.

In conclusion, we observed that the majority of widely adopted apps do not yet feature more automated and technically feasibly DCT's, but still remain at semi-automation.

C. *Cost Aspect*

In our sample 1 app required purchasing before usage, and 10 apps could be downloaded for free (37%). The remaining majority of apps (60%) relied on a freemium business model. That meant that the apps were free to download and provided basic services such as manual entry of food items into diaries, sometimes restricted for a specified trial period ranging from one week to one month. In many cases, more automated data collection techniques or methods were available through in-app purchases. In some cases these additional features were also available for a trial period. Out of the 27 apps, 15 apps required in-app purchases to access all relevant features for diet monitoring, which were purchased for each rater of this review. We think this indicates that app developers have recognized the higher utility higher degrees of automation imply for users.

V. DISCUSSION

The present study explored data collection techniques and their automation among the most popular and publicly available mHealth apps in German speaking countries (N=27). Our findings bear implications for theory, clinical practice and developers, as well as the end user. We end our discussion section with the limitations of our study.

A. *Theoretical Implications*

First, our findings suggest that further assessments and reviews should consider data collection techniques and methods. Specifically, our findings suggest that data collection automation may act as an important moderator on the relationship between mobile health interventions and their desired outcomes. These findings hence also corroborate previous review studies that have underscored the impracticality and inaccuracy of manual data collection techniques and methods [18], [19]. In this vein, future studies and reviews could also consider other meaningful proxies such as attrition rates, user engagement, underreporting or logging accuracy for example, as well as new types of biases that may arise from using more automated data collection techniques. We hope that the overview of DCT's developed in this study can provide a useful starting point for such studies.

Fig. 3 Distribution of DCT's by App

Distribution of DCTs within Application Sample (N=27)

		App ID																										
DCT	ID	5	7	15	16	23	26	21	6	3	1	20	2	13	8	9	10	11	19	24	4	12	17	22	25	27	14	18	Σ
SENSE	7	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	1	2
RECEIVE	6	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
CAPTURE	5.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	5.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	2
RECORD	4.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	4.1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1
SCAN	3.2	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
	3.1	0	0	0	0	0	0	0	1	1	0	0	0	0	1	1	1	1	1	0	1	1	1	1	1	1	1	1	15
SELECT	2.2	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0	0	1	1	1	1	1	1	1	1	11
	2.1	0	0	0	0	0	0	1	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	18
ENTER	1.2	0	0	0	0	0	0	0	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	17
	1.1	0	0	0	0	0	1	0	0	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	19
	Σ	0	0	0	0	0	1	1	1	1	2	3	4	4	4	4	4	4	4	4	5	5	5	5	5	5	6	8	

Second, our findings also point to the lack of more automated data collection techniques in the public landscape. The promise of higher levels of automation for clinical practice, users and researchers (e.g. improved accuracy, user adherence to nutritional interventions) hence warrants further research in this area. Especially in the areas of semi-automated DCT's such as recording and voice-based data collection techniques that did not feature among the sampled apps.

Finally, our findings may have particularly interesting implications for just-in-time interventions (JITAIs) [44], as such interventions are highly dynamic and complex and rely on continuously obtained user data and nutrition interventions [45]. Although JITAIs can be administered through several systems (e.g., in-person, computer), advancements in smartphone technology that allow for continuous in-the-moment participant monitoring and delivery of personalized coping strategies, make mobile devices particularly well-suited for delivering JITAIs that are feasible and scalable. As such, future research could examine the interplay of different data collection techniques, or the potential to reduce or completely remove the need for manual data input, as more data about an individual's dietary intake is captured automatically [18].

B. Implications for Practice and Research

Our findings also suggest different implications for practitioners in the field. First, this review found that data collection techniques and especially data collection methods can vary considerably. Physicians and dietitians should therefore carefully consider them, as some techniques or methods may be more suitable to specific user groups than others (e.g. specific disabilities, degree of nutritional literacy). For example, less nutritionally literate people may profit from capture-based techniques and methods, whereas sensing based techniques can support less self-disciplined users at continuous diet monitoring. These considerations may improve patient data, in turn enabling more targeted diet interventions.

Moreover, the study showed that currently popular diet apps do not take full advantage of today's technology, despite their potential to improve user attrition rates and user engagement. In the short term, developers could profit from automation by for example including more data collection methods of techniques already in use, or by adopting voice-based logging [20], grocery receipts scanning [28], or loyalty-card data feeds [46], which do not require additional hardware purchases for the user. In the medium term, developers are advised to experiment with new DTC's as they promise means to make apps more personalized, accurate and effective, in turn prolonging user engagement.

Third, our findings may also point to the need for governmental stakeholders to regulate retailers and payment providers to allow or facilitate consumption data retrieval for users in form of digital receipts. Successful examples indicate that such technical data feeds enable novel automatic mHealth systems [46]. Since such regulation is not present in Germany or most Western countries, retailers and payment providers are shielding purchase data away from mHealth developers and users.

C. Implications for mHealth App Users

Finally, our study also provides practical insights for users. Our review included free as well as expensive apps, with some applications resulting in significant costs on the user. However, even free apps (e.g. Samsung Health) were able to achieve similarly high ratings in app quality and convenience (automation), when compared to more expensive applications (e.g. Lifesum). Moreover, if it is the user's intention to change his diet with the help of mHealth apps, he or she should also consider automation and related data interfaces aside from app quality and cost considerations.

D. Limitations

In our opinion, this review only provides modest insight about the usefulness or types of utility gained from automated data collection means. To address this limitation, future research could for example consider frequency of occurrence [14]. Further criterions to consider may be accuracy or time saved, which we estimated less systematically during the testing of the sample applications. It would be interesting to perform a quantitative evaluation study for this particular issue.

VI. CONCLUSION

The present study explored DCT's and their automation among a set of popular and publicly available mHealth apps. Our contributions are threefold. First, we provide a more comprehensive taxonomy of DCT's, compared to earlier reviews. A second contribution lies in its application in the review of well-adopted and publicly-available apps, where we found that although a multitude of DCT's and methods are increasingly becoming available, more novel and automated data techniques, suggested in the literature, still remain nascent in commercial use. For example, in contrast to previous app reviews, we observed some diffusion of semi-automated data collection techniques beyond barcode scanning systems, including the application of computer-vision and wearable based assessments. This finding underscores the ongoing diffusion of increasingly automated data collection techniques from laboratory environments to practice. Moreover, we found that camera and sensor-based data collection techniques will require the adoption and diffusion of relevant hardware on the user side (e.g. smart-plates, special spatulas, wearables) for these techniques to diffuse. Finally, our findings highlight the need to better understand data collection in mHealth applications to improve user adoption, interventions and user engagement.

A focus on DCT's is not only important to ensure app-based interventions are tailored to address specific user needs, but is also timely, as the uptake of mHealth services are expected to increase in young adults and supersede more traditional forms of treatment. Therefore, it is necessary for clinical practice to develop a more comprehensive understanding of the value of different DCT's, diet apps may have to offer. Moreover, further research can allow for the development of common measures to better understand the role and impact of automation in mHealth, which to the best of our knowledge so far has not substantially featured in previous app reviews.

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