Automation of Data Collection in diet-related mHealth: a Review of Publicly Available and Well-Adopted Apps

Completed Research Paper

Introduction

Strong evidence exists that link the global shift toward high calorific diet patterns to the spread of diet-related chronic diseases, such as obesity, hypertension or diabetes (Popkin 2002). The epidemic increase of diet-related non-communicable diseases represents a significant burden for patients and healthcare systems around the world due to its cost-intensive medical treatments and increased rates of mortality. However, due to limited financial and personnel resources, the majority of population cannot be included in contemporary countermeasures (Kushner 1995). As diet-related mobile health applications (mHealth) promise to be an inclusive, scalable and supportive conduit to health behavior change and healthy lifestyles (Brug et al. 2005; Vandelanotte et al. 2016), there is an ever-growing body of research as well as an impetus from practitioners aiming to provide users and patients with evidence-based mHealth interventions in form of convenient, low-cost and personalized diet self-management tools.

Unfortunately, current mHealth's effort-intensive manual entering of nutritional intake is responsible for underreporting of nutritional intake (Svensson and Larsson 2015) due to memory and recognition biases, excessive user attrition (Brindal et al. 2012; Laing et al. 2014), as well as a self-selection of interested, often healthy users (Williamson et al. 2006). At the same time, the rapid and ubiquitous uptake of smartphones with a variety of sensors and related technologies enables several novel automated data collection techniques for diet monitoring that promise higher accuracy or convenience, compared to traditional manual entry methods (Franco et al. 2016; Steele 2015). Hassannejad (2017) for example reviewed the potential of various imaged-based approaches to identify and quantify foods. Whereas Vu and colleagues (2017) provide an overview of different non-wearable and wearable sensing technologies and data analytical approaches including motion or acoustic based methods that allow to detect food intake related variables beyond food type and quantity.

However, to date, research on the implementation, diffusion and interplay of automated and manual data collection techniques in diet-related mHealth applications remains in a nascent state, as first, randomized controlled trials are only available for very few applications, and second only three app reviews have so far assessed an incomplete, selected subgroup of data collection techniques across diet applications, and third, research on automated data collection usually exclusively focus on not publicly available apps or purely conceptual studies, without the use of qualitative or quantitative analysis of publicly available app content, which many researchers, users and application developers rely on. Such a perspective 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 data collection techniques diet apps may have to offer. While simultaneously further research can allow for the development of common measures to better understand the role and impact of automation in mHealth, which so far has not substantially featured in previous app reviews.

To provide more insight regarding the afore-mentioned gaps, we thus conducted an app review that consisted of the 22 most popular diet apps in the German speaking area. We examined both the degree of automation of these apps, based on a self-developed measure from an extensive literature review, as well as its effect on perceived app quality (Mobile App Rating Scale (MARS) (Stoyanov et al. 2015)), measured with a one-way ANOVA. We find that the currently most popular and well adopted apps still rarely integrate rather automated or fully automated data collection techniques, but when they do it appears to correlate with and potentially lead to significantly higher perceived app quality. In other words, our findings suggest that - what we refer to and define in this study as - 'the degree of automation' can explain for variance found in perceived app quality. We discuss the implications for theory and practice and identify research-practice gaps that hopefully stimulate the development of new and more sophisticated diet apps.

Table 1. Overview diet related app reviews (2015-2018)			
Study	**Apps**	**Review focus**	**DCT**
Zapata et al. (2015)	22	Design, Functions	No
DiFilippo et al. (2015)	4	BCT	No
Fairburn and Rothwell (2015)	39	BCT, Functions	No
Subramanian (2015)	89	BCT, Design, Functions, Tailoring	No
Darby et al. (2016)	42	Data Collection, Functions, Tailoring	Yes
Davis et al. (2016)	10	BCT	No
Franco et al. (2016)	13	Data Collection, Functions	Yes
Rivera et al. (2016)	393	Functions	No
Zaidan and Roehrer (2016)	51	Design, Functions	No
Rohde et al. (2017)	3	Data Collection, Design, Functions, Gamification	Yes
Schoeppe et al. (2017)	5	BCT, Functions, Design	No

Table 1. Overview of diet-related app reviews

Related Work

Data collection in mHealth

There has been much contention about the effectiveness of publicly available diet-related mHealth apps to improve or support a user's diet. For example, a review by Harris et al. (2011) concludes that online interventions to promote dietary behavior can be at least as expensive as traditional behavior change interventions and do not produce clinically significant improvements. More recently, reviews have become more positive about the effectiveness of self-directed online weight loss interventions (e.g. Coughlin et al. 2015; Flores Mateo et al. 2015; Gasch et al. 2016; Hou et al. 2014; McCarroll et al. 2017; Vandelanotte et al. 2016). Still, most meta-reviews report small effect sizes, large variety in app content, design and outcomes (Cushing and Steele 2010; Müller et al. 2016).

To better understand such outcomes, mHealth reviews to date have sought to examine an array of individual components of mHealth apps. For example, a large body of work has highlighted the need for behavioral theories and essential functions in mHealth apps (table 1). Other studies have examined the perceived quality of mHealth applications (Schoeppe et al. 2017; Zaidan and Roehrer 2016; Zapata et al. 2015), mostly seeking to rate apps based on their engagement, functionality, informativeness and design properties (Stoyanov et al. 2015). More recently, gamification approaches have been applied and studied to diet-related apps, as gamification is increasingly viewed as a promising way to promote the use of mHealth systems (Hamari et al. 2014; Thiebes et al. 2014; Rohde et al. 2017).

However, only few studies so far have considered data collection techniques within dietary app reviews (see table 2). This is curious in so far that lack of engagement has been raised as a key concern across studies. For example, Mateo and colleagues (2015) suggest that diet-related apps must become engaging in more relevant ways during usage and less effort-intensive. Laborious manual entering of nutritional intake represents a key reason for underreporting of nutritional intake (Kikunaga et al. 2007; Lissner 2002; Svensson and Larsson 2015), excessive user attrition (Baranowski et al. 2008; Brindal et al. 2012; Eysenbach 2005; Laing et al. 2014; Wardle et al. 1999), and a barrier leading to exclusion of users with low motivation, especially in demographic segments that are predestined for obesity (Williamson et al. 2006).

Novel, more convenient and more automated data collection methods promise to ameliorate this situation, as such methods can be faster, less effort-intensive for users, and potentially even more accurate (Hassannejad et al. 2017; Vu et al. 2017). In addition, the integration of automatic data collection techniques also allows for improved persuasive personalization or tailoring of dietary behavior change interventions onto the individual mHealth current user's state. Such context-tailored just-in-time adaptive interventions, such as congratulating a user upon finishing a healthy meal (Mohr et al. 2014; Riley et al. 2011; Spruijt-Metz and Nilsen 2014), are increasingly perceived as a key advantage over traditional nutritional education campaigns (Brug et al. 2003, 2005; Orji 2014), especially when not actively triggered, but passively initiated without user input during a state of receptivity that was sensed through automatic data collection techniques (Goldstein et al. 2017; Hassannejad et al. 2017; Hekler et al. 2013; Nahum-shani et al. 2014; Thomas et al. 2015). Despite this potential, data collection and its automation degree have received far lesser attention in diet-related mHealth app reviews, compared to other app components (cf. table 1).

Data collection techniques (DCT)

A variety of alternative data collection techniques 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 comfort, accuracy, advantages and challenges (Hassannejad et al. 2017; Rusin et al. 2013; Steele 2015; Vu et al. 2017). However, data collection techniques so far have not substantially featured in mHealth app reviews (table 1). In fact, only three reviews have compared diet applications by data collection technique (table 2). Unfortunately, none of them has assessed all available data collection techniques among their mHealth sample, we hence provide an overview of all previously reviewed data collection techniques in the following.

Table 2. Existing app reviews of data collection techniques in diet-related mHealth

Author	Apps	Assessed data collection techniques						
		Entry	Select	Scan	Record	Capture	Receive	Sensing
Darby et al. (2016)	42	●	●	●	●	**n.a.**	**n.a.**	●
Franco et al. (2016)	13	●	●	●	○	○	**n.a.**	**n.a.**
Rohde et al. (2017)	3	●	●	●	**n.a.**	●	**n.a.**	**n.a.**

● : DCT assessed   ○ : DCT assessed, not found in sample   **n.a.** : DCT not assessed in review

Table 2. Existing app reviews of data collection techniques in diet-related mHealth

Manual entry for each food item ("Entry")

Manual entries on mHealth apps represent a common data collection method, similar to traditional handwritten self-reports (e.g. 24h food recall diaries). Systems relying on manual entry require the user to individually enter each food item and the amount consumed through manual text input (Darby et al. 2016; Vu et al. 2017). While manual entries are widely applied within mHealth systems and require little user education (Darby et al. 2016; Franco et al. 2016; Rohde et al. 2017), text-based entry methods also heavily rely on conscious record-keeping, recall and memory. These characteristics lead to underreporting and user attrition (Martin, 2009). Hence, some mHealth apps have introduced supporting functions such as auto-completion of text input, bookmarking of preferred food items, search functionality within food item databases, thereby reducing the manual effort to search for food items (Darby et al. 2016; Rohde et al. 2017).

Manual selection of preconfigured multiple item combinations ("Select")

For certain mHealth apps, relevant food items might be compiled into food record checklists (Beer-Borst et al. 2017) or food frequency questionnaire (Timon et al. 2017) or recently used food items, to suggest a finite number of food items to the user from which one or multiple consumed items can be selected. Thereby, such mHealth applications reduce search costs, offering less effort-intensive food logging, as the user only selects from a limited number of relevant food items to reliable self-report dietary intake (Brooke and Thompson 2013; Chow et al. 2016; Kristal et al. 2014; Labonté et al. 2012; Morin et al. 2005) *(DCT Method 2.1)*. Similarly, also to lower the effort involved in manually logging food items, some dietary mHealth apps have integrated the option to select from a pre-configured or configurable combination of food items, e.g. the user creates or selects a complete recipe or meal that was consumed (Steele 2015), rather than each food item separately (Darby et al. 2016). This data collection technique is also referred to as multi-add tool (Darby et al. 2016) or creation of own meal items (Franco et al. 2016; Rohde et al. 2017) *(DCT Method 2.2)*. The challenges with selecting items from food-record checklists or configurable meals are that predefined items might differ from actually consumed items and that the selection process still requires several interactions daily, in order to maintain a continuous self-reported dietary protocol.

Scanning an optical item identifier ("Scan")

Packaged grocery products usually feature a barcode identifier, commonly referred to as Global Trade Item Number (GTIN) or Universal Product Code (UPC) (Carol Byrd-Bredbenner 2010). Therefore, some diet-related mHealth apps feature barcode scanning functionality (Darby et al. 2016; Franco et al. 2016), through which a user can conveniently identify a consumed product by scanning its identifier (Franco et al. 2016). Unfortunately, product identifiers may not always be available. For example, not all food items contain barcodes (e.g. unpackaged fruits and vegetables), and users cannot rely on barcodes when eating out. Still, when they are to be found, barcode scanning represents a powerful and unambiguous data collection technique (Franco et al. 2016). In order to aggregate consumed products and reduce the number of necessary scans, some apps have begun integrating Object Character Recognition (OCR) to interpret printed supermarket receipts and query relevant data for multiple products in one scan process (FoodCache 2018; Steele 2015). The main challenges with barcode scanning are incomplete food composition databases and insufficient data quality, which can substantially falsify user's dietary intake. 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.

Voice recording and natural language processing ("Record")

With the growing popularity of smartphone embedded voice assistants such as Apple Siri, users increasingly engage with applications via voice. As the voice to text transcription eases the effort involved in logging food items (Darby et al. 2016), voice recordings and language processing seem promising, yet rarely seen so far in dietary mHealth apps. 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.

Applying visual computing to identify a meal's characteristics ("Capture")

With the recent progresses of visual computing (Krizhevsky et al. 2012), automatically deriving a meal's characteristics and quantity from a picture or video became technically feasible (Hassannejad et al. 2017; Vu et al. 2017), and has been integrated in diet-related applications (Myers et al. 2016; Rohde et al. 2017). Primary elements of visual computing based intake assessments are the segmentation and quantification of meal components (Hassannejad et al. 2017). Although improvements to visual computing research are constantly achieved, the technology is still under active development and recognition rates of items and quantities remain limited (Hassannejad et al. 2017). At its current state image-based capturing remains semi-automatic, as users actively capture an image and may have to confirm correct meal identification (Hassannejad et al. 2017). In the future, camera enhanced smart-glasses (Epstein 2015) or smart-plates (Smartplate 2018) might become able to continuously monitor user activity for relevant food items and passively detect composition and quantities automatically, without any additional required user input.

Data feed from purchase logs that include food items ("Receive")

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 (Brinkerhoff et al. 2011a; Steele 2015).

In some countries, over 80% of the revenue of a retailer can be attributed to individual loyalty accounts (Accarda 2005; Handelszeitung.ch 2004). This data could be extremely valuable for diet and habit monitoring when combined with food composition product databases (Brinkerhoff et al. 2011b; Chidambaram et al. 2013; Coll 2013; Eyles et al. 2010; Illner et al. 2012). When purchasing data is collected automatically instead of manually, such data feeds offer a completely effort-less automatic data collection technique. Yet, its accuracy depends on estimation models that can account for circumstances such as household level data or restaurant visits. These challenges have led some to recommend the combination and calibration of digital receipts with other accurate data collection techniques, such as self-reported diaries (cf. Steele 2015).

Detection of eating activity through wearables or external sensors ("Sense")

Due to advances in the miniaturization of devices, detection of diet-related activities becomes increasingly feasible through an ever smaller and ubiquitously available range of wearables or non-wearable sensors (Hassannejad et al. 2017; Vu et al. 2017). Such devices can monitor arm gestures, swallowing or chewing activity through means of electroglottography (EGG) or electromyography (EMG), piezoelectric charge, accelerometers or acoustic microphones (Hassannejad et al. 2017; Vu et al. 2017). Many ideas have been proposed from pressure-sensitive tablecloths (Vu et al. 2017), sensor-based spatulas (Habibovic et al. 2018) or beverage cups (Zimmermann et al. 2017). 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 more accurate data collection techniques (Vu et al. 2017). Sensor-based dietary activity detection can be 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 (U.S. Food and Drug Administration 2016).

Methodology

In order to assess the data collection techniques in popular apps, we collected an exhaustive list of alternative data collection techniques based on the recent app reviews (Darby et al. 2016; Franco et al. 2016; Rohde et al. 2017) and technology review papers (Hassannejad et al. 2017; Steele 2015; Vu et al. 2017), and weighted each technique with an automation score (see Data Collection Techniques). In order to explore the adoption of the different data collection techniques in publicly available and widely adopted dietary mHealth apps, we resembled a layman's search approach and sampled relevant mobile apps and assessed their implemented data collection techniques. Next, each app's perceived quality was rated by a four-people expert panel (two dieticians, two IS researchers) through application of the Mobile App Rating Scale (MARS). Lastly, we assessed whether apps with increased automated collection techniques were perceived of higher quality when compared to less automated applications through a one-way ANOVA.

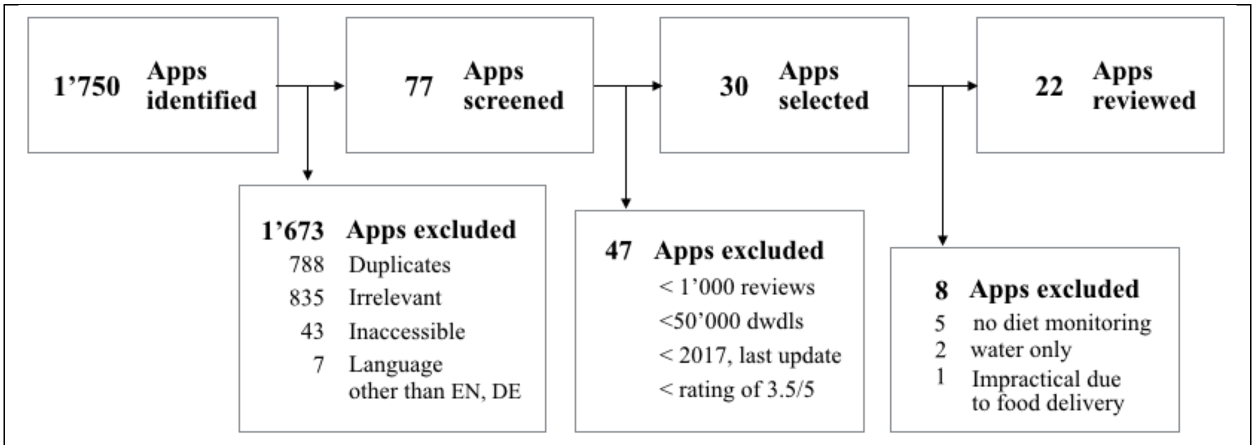

Figure 1. App selection process (PRISMA)

App Sampling

Our systematic sampling approach follows the four-phase PRISMA process (Anderson et al. 2016) (figure 1). 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", as well as the combinations "healthy diet", "food coach" and "nutrition coach" into the German Google Play store. We decided to limit our search to the Google Play store, as Android represents the dominant mobile operating system in Germany with a market share of over 65% (Statcounter 2018). The sampling was conducted in Q4/2017, where we identified 1'750 apps, based on the app store's search output. In a second step, a pre-screening led to the exclusion of 1'673 apps, which consisted mostly of duplicates that appeared across search terms or apps that clearly were not intended for nutrition interventions (e.g. social media apps, calendars, games, learning apps). In a third step, 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 (last update prior to 2017), or a user rating lower than 3.5 out of 5. This screening led to a shortlist of 30 apps. Lastly, we realized that two apps only measured water intake and another app required continuous meal purchases to measure nutritional intake. Five further apps did not use any data collection technique at all. We hence dropped these apps for reasons of irrelevance and cost-efficiency. Ultimately, we reviewed a total of 22 apps, of which almost all relied on a freemium business model (see table 4).

Data Collection Techniques (DCT)

mHealth apps collect dietary intake data to assess a user's dietary situation and ideally provide adequate nutritional interventions. Our literature review illustrated that data collection mechanisms in research are manifold, ranging from purely manual methods (e.g. food diary, food frequency questionnaires), to fully automated methods that involve wearable and non-wearable sensor technologies. Because data collection techniques so far have not featured substantially in past app reviews, we developed the following list of data collection techniques, which also include recently made available approaches. The seven DCTs and their rather manual versus rather automated implementation alternatives have been derived from and introduced in the literature review. The classification was achieved in collaboration with dieticians and IS researchers and automation degrees were attributed to each DC methods under consideration of the required user input under realistic circumstances. This approach rendered seven techniques and 14 sub-methods (see figure 2). These functions were assessed in all apps based on the complete list. As many apps reviewed contained a combination of data techniques and methods, we accounted for the benefits of increased automation by weighting in order to better assess whether an app manifested a lower or higher 'degree of automation'. Specifically, we weighted each step of automation (*fully manual*, *rather manual*, *semi-automatic*, *rather automatic*, *automatic*) on a 1-5-Likert scale respectively, and explain each classification from our scale under Degree of Automation.

Degree of Automation

We drew on Rusin et al. (2013) classification to determine the degree of input automation, from 'manual', to semi-automatic and fully automatic, but increased the nuances by application of five degrees of automation. The 'Entry' and 'Select' based data collection techniques can be classified as manual input techniques (Rusin et al. 2013). With 'Entry' techniques we further differentiate between '*fully manual'* and '*rather manual'* methods. Methods that require users to type food items within the app (e.g. user has to type "almonds", "1 bar") are considered to be '*fully manual' (DCT Method 1.1)*. Whereas technically more sophisticated, supportive text input systems *(DCT Method 1.2)* such as predictive auto-text-completion that accelerate the manual entry process (e.g. user begins typing "chocolate" and relevant suggestions appear) are considered '*rather manual'*, because they still take significant time and effort when logging multiple times per day. Selection techniques consist only of '*rather manual'* methods as predefined food record checklists (e.g. user confirms to have drunk a glass of water within the app) *(DCT Method 2.1)* or preconfigured item combinations (e.g. user confirms to have eaten a certain recipe within the app) *(DCT Method 2.2)* do away with entry but still require the triggering of the logging process and correctly identification and quantification.

Scanning, recording, capturing and receiving based techniques include '*semi-automatic'* input techniques, when methods still require some form of input by the user, in form of manual quantity specification or actively capturing or recording meals or receipts for example (Rusin et al. 2013). For example, scanning of product barcodes *(DCT Method 3.1)* or receipts *(DCT Method 3.2)* are considered '*semi-automatic*' data collection methods, as they automate important parts of the food logging process such as the food item identification. Likewise, voice-based food logging eases the effort to identify items, as machine learning based classification algorithms identify food items with accuracy rates of over 90% (Lacson and Long 2006). If the user needs to actively capture each meal *(DCT Method 4.1)*, the method is considered '*semi-automatic*' as well. The same principle holds for capturing and receiving. Capturing image or video to identify and log diets is considered a *semi-automatic* process, if the process still needs to be initiated frequently by the user *(DCT Method 5.1)*, as the mHealth system only conducts the correct identification and quantification but demands interaction of the user. Digital receipt data feeds - despite potentially aggregated data, - still allow for inference about consumed items. Therefore, if actively triggered (e.g. sharing a single digital receipt from a payment to a diet app manually), this method *(DCT Method 6.1)* is considered '*semi-automatic*'.

Table 3. Data collection techniques and methods

DCT	Description	DCT Method	DoA
1. Entry	Manual entry for each food item	1.1 Text entry per food item	fully manual
		1.2 Supported text entry	rather manual
2. Select	Selection of preconfigured item combinations	2.1 Selection from item shortlist	rather manual
		2.2 Select pre-/configurable meals	rather manual
3. Scan	Scanning an optical item identifier	3.1 Scanning a product barcode	semi-automatic
		3.2 Scanning a printed receipt	semi-automatic
4. Record	Using voice recording to log food items or meals	4.1 Actively started voice log	semi-automatic
		4.2 Passively started voice prompt	rather automatic
5. Capture	Image based visual computing to identify meal	5.1 Actively capture meal image	semi-automatic
		5.2 Passively captured meal image	fully automatic
6. Receive	Data feed from purchase logs that include food items	6.1 Share a digital receipt with app	semi-automatic
		6.2 Automatic digital receipt feed	fully automatic
7. Sense	Detection of eating activity through wearables/sensors	7.1 Manual sync of sensors to app	rather automatic
		7.2 Auto-sync of sensors to app	fully automatic

Table 3. Data collection techniques and methods

Finally, '*fully automatic*' input techniques ideally do not require any action of the user. Automated processes can be found with record, capture, receive and sensor-based techniques. For example, if an automated system recognizes eating activity and prompts users to voice-log the current meal *(DCT Method 4.2)*, the method is considered *rather automatic*, as memory and recall biases are minimized. Similarly, automatically captured and interpreted image or video material from smart-glasses or smart-plates is considered '*fully automatic*' *(DCT Method 5.2)*, as it triggers the process independently. When purchase records from the own loyalty card are automatically synchronized *(DCT Method 6.2)* like the Discovery mobile app from South Africa (Discovery 2018) the method is also considered '*fully automatic*'. As well as sensor or wearable based methods that are also considered '*fully automatic*'. Also, even though differences depending on whether a sensing technique requires active synchronization effort *(DCT Method 7.1)*, or not *(DCT Method 7.2)*, when a user for example wears a sensor that detects chewing motion automatically, both forms of synchronization allow logging multiple consumed food items or diet-related activities at once. Hence, we subsumed both methods as '*fully automatic*'.

App Quality and Statistical Analysis

To assess the effect of automation we relied on the Mobile App Rating Scale (MARS) framework, which is an established mHealth app quality assessment and has been applied in multiple review studies (Stoyanov et al. 2015). The MARS framework contains 19 items on a 5-point Likert scale (1=inadequate, 2=poor, 3=acceptable, 4=good, and 5=excellent) to assess (perceived) app quality. Items are grouped into four subscales: engagement (5 items), functionality (4 items), aesthetics (3 items), and information quality (7 items). The average of the four scales eventually determines the app quality score. Five independent reviewers - composed of one dietitian and four IS researchers - participated in rating the app quality via MARS. As recommended, all raters participated in a workshop regarding the application of the framework prior, and intra-class correlation coefficients over 70% for each subscale per two-way random model were obtained. The average quality of diet apps scored well above acceptable (mean 3.9), which may relate to their popularity. Interestingly, in regard to the MARS sub-scales, the observed diet apps performed worst in terms of engagement (mean = 3.62, SD = 0.71), compared to functionality (mean = 4.09, SD = 0.37), aesthetics (mean =3.93, SD = 0.75), and information quality (3.94, SD = 3.94(0.52). We provide an overview of apps and their perceived quality in table 4. Finally, we applied a one-way ANOVA to assess whether significant differences in quality were attributable to different levels of automation observed.

Table 4. Quality and cost assessment of app sample

No	App	Quality score	Costs (qtly, USD)	No	App	Quality score	Costs (qtly, USD)
1	8fit Workout	4.48	30	12	CodeCheck	3.82	2.9
2	Lifesum	4.4	28.25	13	Lose it!	3.78	9.45
3	Weight	4.25	51	14	Fat Secret	3.74	Free
4	Samsung Health	4.18	Free	15	Fooducate	3.73	17.7
5	Fitbit	4.14	Free	16	Barcoo QR	3.58	Free
6	MyFitnessPal	4.13	35.3	17	Kalorien	3.46	21.1
7	Noom Coach	4.04	141.25	18	My Diet Diary	3.45	Free
8	YAZIO	3.98	23.5	19	Life Balance	3.4	1.5
9	Calorie Counter	3.92	15.75	20	Nährwerte	3.33	Free
10	Meine Diät	3.87	14.15	21	Abnehmen ohne	3.25	3.5
11	FDDB	3.85	Free	22	WeightWar	2.97	14.75

Table 4. Quality and cost assessment of app sample

Findings

General Characteristics of the mHealth sample

Out of the 22 apps reviewed apps, with the exception of one app all of them 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. The vast majority of apps were free to download and often provided basic services such as manual entry of food items into diaries. In many cases, other data collection techniques or methods were available through in-app purchases. Out of the 22 apps, 15 apps required in-app purchases to access all relevant features for diet monitoring (see table 4), which were purchased for each rater of this review.

Automation of Implemented Data Collection Techniques

Manual Entering and Selection based techniques represented the most widely adopted data collection techniques (86%, 19/22), see table 4. 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 use data collection techniques, most notably by means of auto-completion of text input and predictive text search options. In regard to selection mechanisms (86%, 19/22), almost all apps relied on the 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 insights suggest that developers acknowledge the need for more user-friendly and personalizable DC methods, 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. Moreover, a total of 14 apps made use of scanning-based DC methods for diet monitoring (14/21, 64%). 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 maz be that this method has only recently been implemented in end-user applications (FoodCache 2018; Steele 2015). 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.

Capturing and Sensing belonged to the least common techniques applied among the observed apps. Capturing featured among 2 apps (9%, 2/22), and required the user to actively take and confirm images and image recognition (2/2). None of these app assessed image or video data automatically (0/2). Sensing on the other hand, maybe surprisingly, only featured in two apps (9%, 2/22), directly related to dietary behavior. In one case, it required the user to actively sync the data (Lose It) (1/2), in the other case the data syncing was automated from the glucose monitoring device (Samsung Health, Dexcom) (1/2). 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 (64%, 14/22), yet are traditionally not considered primarily relevant data in diet monitoring studies.

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 that are easily interoperable. Furthermore, none of the apps used voice recording based dietary logging, neither actively triggered within the application, nor with passively triggered automation mechanisms. The absence of recording-based techniques appears striking in so far that voice-to-text transcription 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.

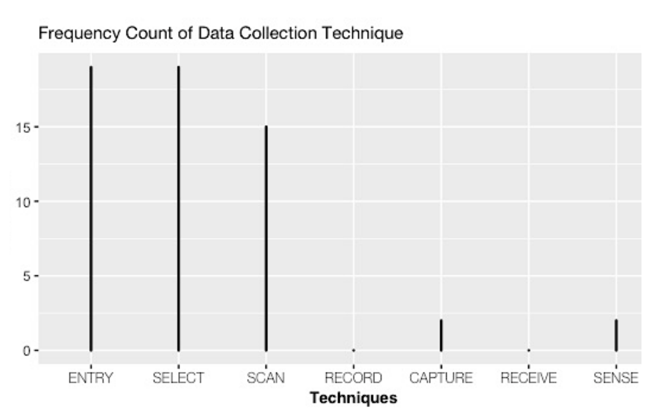

Figure 3. Distribution of observed data collection techniques

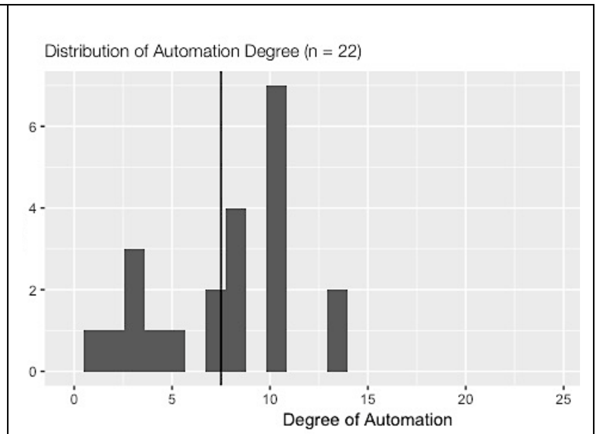

Figure 4. Histogram of observed apps' degrees of automation

While only one app relies on completely manual text input (5%, 1/22), all other apps make use of at least some sort of technologic input support (95%, 21/22). Interestingly, while apps included on average a combination of 3.8 separate data collection methods, only 16 apps (72%, 16/22) included at least one semi-automatic or fully automatic DCT method. Surprisingly, only two apps (9%, 2/22) utilized automatic or fully automatic data collection techniques. To assess the impact of automation in more detail, we calculated a degree of automation for each app, as defined earlier. We weighted each app's DCT Methods by its degree of automation (1=*fully manual*, 2=*rather manual*, 3=*semi-automatic*, 4=*rather automatic*, 5=*fully automatic*) from 1-5 respectively, and calculated a sum of all applied DCTs for each app. As Hassannejad et al. (2017), Steele (2015) and Vu et al. (2017) explain, the fusion of established and automated data collection methods are desirable in dietary monitoring, therefore each mHealth system's degree of automation is calculated by its sum of automation-weighted data collection methods represented within its app (figure 5). As there are 7 DCTs with a total of 14 Methods ranging from 1=*fully manual* to 5=*fully automatic*, each mHealth's degree of automation lies between 0 (=no data collection technique integrated) and a theoretically possible score of 45 (=all DCTs integrated).

Impact of Data Collection Technique on Perceived App Quality

The review detected a very low average of automation degree at 16% (7.4/45) and median of 18% (8/45) (figure 5), which explains why the distribution of automation degrees among the sample is right-skewed (figure 4). The spread of automation degrees can be clustered into two groups: apps that received scores below 7.4 solely relied on manual data collection techniques, and apps that received higher scores either included semi-automatic or automatic techniques, aside from primarily manual data collection techniques (see figure 4).

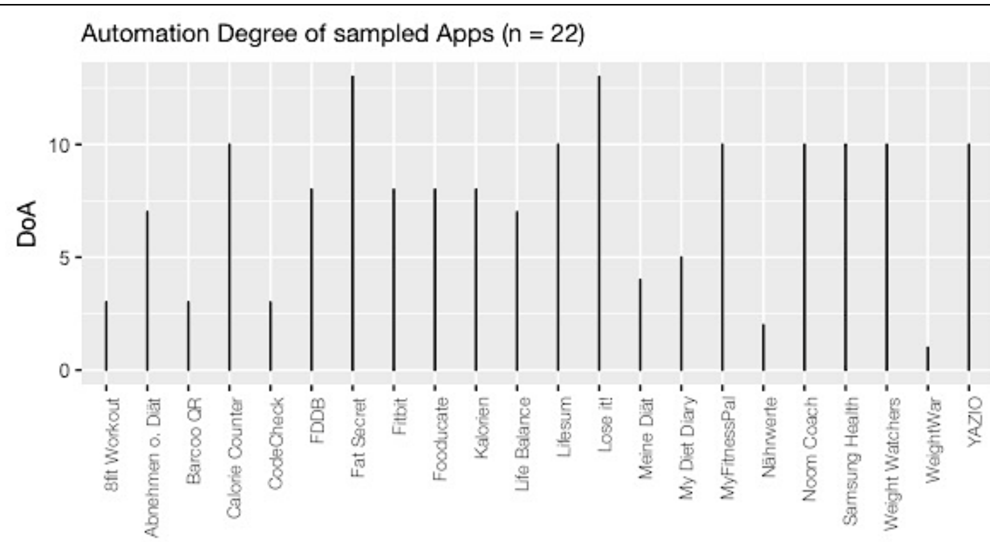

Figure 5. Distribution of app-specific degree of automation scores

Comparing these two clusters in regards to perceived application quality (as assessed by our four experts via the MARS scale), we found a statistically significant difference between the groups as determined by a one-way ANOVA at the $p<.05$ level for the three conditions [$F(1,20) = 7.792$, $p = 0.0113$] (table 5). A post hoc tukey test showed that the group of apps with lower automation degree compared to the group of apps with higher automation degree levels differed significantly at $p<.05$. Taken together, these results suggest that lower levels of automation in diet apps achieve lower perceived app quality scores than higher levels of automation in diet apps.

Table 5. Results of one-way ANOVA

Data collection technique	Df	Sum of Squares	Mean Square	F	Sig.
Between	1	0.01210	0.012105	7.792	0.0113 *

Within	20	0.03107	0.001554		
Total	21	0.04317			
Significance codes: 0 '***', 0.001 '**', 0.01 '*', 0.05 '.'					

Table 5. Results of one-way ANOVA

Discussion

The present study explored data collection techniques and their automation among the most popular and publicly available mHealth apps in German speaking countries and aimed to assess whether apps with higher levels of automation in regard to data collection improve perceived app quality. Our findings are threefold. First, our findings suggest that although a multitude of data collection techniques and methods are increasingly becoming available, more novel and automated data techniques suggested in the literature still remain nascent in commercial use. This was to be expected for most camera and sensor-based data collection techniques, as their adoption and diffusion within the most popular diet-related mHealth applications require the adoption of relevant hardware on the user side (e.g. smart-plates, special spatulas, wearables). Surprisingly, record, scan and receipt-based techniques do not yet feature in well adopted mHealth apps, despite their previous implementation in publicly, but less adopted mHealth apps, and promising convenience in diet logging. Second, 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. Finally, and maybe most importantly, our findings suggest that more automated data collection positively perceived app quality. This is striking, giving that the automation degree levels assessed remained overall modest. Suggesting that already small steps toward automation can render statistically significant effects. These findings have noteworthy theoretical and practical implications and point to interesting future research, which we discuss in the following.

Theoretical Contributions

First, our findings suggest that further assessments and reviews should consider data collection techniques and methods. As 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 of manual data collection techniques and methods (Steele 2015; Vu et al. 2017). 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 automation degree scale developed in this study can provide a useful starting point for such studies. 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 recording and receipt-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), as such interventions are highly dynamic and complex and rely on continuously obtained user data and nutrition interventions (West et al. 2012). 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 even completely remove the need for any manual data input, as more data about an individual's dietary intake is captured automatically (Steele 2015).

Practical Relevance

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. 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. Second, most fully automated data collection methods rely on sensor hardware, leading to a need for financing such hardware. A potential consequence for treatment or management of diet-related diseases could be the provision of such hardware (e.g. wearables, smart-plates, smart-cups) to patients by their health-insurance. Future work is needed to assess the effectivity and financial feasibility of such measures, but since similar approaches have rendered beneficial in physical activity interventions, similar solutions should be assessed for dietary interventions (Forbes 2018). Third, 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 (Darby et al. 2016), grocery receipts scanning (FoodCache 2018), or loyalty-card data feeds (Discovery 2018), which do not require additional hardware purchases for the user. In the medium term, developers are advised to experiment with new data collection techniques. As the later promise means to make apps more personalized and effective, in turn prolonging user engagement. Fourth, 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 (Discovery 2018). 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. 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 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.

Limitations

The exclusion of not publicly available apps represents a key limitation of this study and limits the generalizability of the results. For one, the app criteria may have led to the exclusion of apps with more automated data collection techniques, or ones that did not feature in our app review (e.g. loyalty card data). Further studies may hence apply a sampling strategy that renders a higher heterogeneity in regard to techniques and methods. Second, the sampling criteria may have led to a systematic selection bias against apps with a greater potential for diet self-management improvement. This point closely ties in with another limitation. 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 (Rusin et al. 2013). 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. Finally, our framework for assessing the degree of automation for the most part only considered food type and quantity. Further research should also consider data collection on indirect but maybe equally important factors for diet self-management such as physical activity, mood, location or speed of eating.

Conclusion

This study builds upon first app reviews that have begun to consider data collection techniques and methods as an important factor to increase user engagement and improve nutritional intervention outcomes. Such a perspective 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. Specifically, this study set out to explore 22 popular diet-related mHealth apps based on the type and degree of automation of their data collection techniques. To this end, we developed a multidimensional, reliable, and flexible rating scale for researchers, developers, and health-professionals to assess degrees of automation in data collection. Applying this scale, we found overall low levels of automation among highly popular apps. Still, apps that relied on more automated data collection techniques (e.g. barcode scanning or wearables) appeared to feature higher perceived app quality scores than apps that relied solely on manual techniques ($p<0.05$). These findings provide interesting implications for future app effectivity and (just-in-time adaptive) intervention studies.

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