Is Burden Always Bad? Emerging Low-Burden Approaches to Mobile Dietary Self-monitoring and the Role Burden Plays with Engagement

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Abstract

Objective The goal of this paper is to provide an overview of the emerging lower-burden mobile dietary self-monitoring approaches and provide a case study highlighting the role that habit formation (regularly logging meals) and burden played in two weight loss interventions examining three different methods of dietary self-monitoring: two lower-burden (wearable device and photo-based) and one higher-burden (standard database app).

Methods A review of the literature of current methods for dietary self-monitoring was conducted. In addition, a case study using data from two different remotely delivered weight loss interventions is presented. Participants ($n = 100$) were randomly assigned to one of the three mobile diet tracking methods. At 6 weeks, participants were asked seven questions on a Likert scale (1 completely disagree; 7 completely agree) assessing factors such as habit formation (e.g., remembering to use the device).

Results Several emerging methods of dietary self-monitoring are presented. For the case study, the wearable device (5.0 ± 1.81) and photo-based app (4.0 ± 2.24) participants found it more difficult to remember to use their device than did the standard database app (2.35 ± 1.79 ; $p < 0.001$) participants, indicating that habit formation was stronger in the Standard App condition than the approaches that were aimed to be of lower burden.

Conclusions Gaining a better understanding of the current and innovative approaches to dietary self-monitoring, as well as considering how burden and habit formation may be influencing sustained engagement could help inform future effective dietary interventions.

Keywords Diet · Self-monitoring · Mobile health · Nutrition · Weight loss · Self-regulation · Smartphones · Adherence

Introduction

Dietary self-monitoring is one of the key elements of behavioral weight loss programs (Burke et al., 2011; Linde et al., 2005). The goal of dietary self-monitoring is to modify dietary intake through self-regulation, with the information gleaned from self-monitoring records facilitating the identification of patterns surrounding the context, antecedents, and consequences of consumption of specific foods and beverages, as elucidating context of eating episodes, and providing feedback to enhance self-efficacy for making dietary behavior changes (Mackay, 1980; Schnoll &

Zimmerman, 2001; Watson & Tharp, 1997). Mobile health (mHealth) has the potential to increase the frequency of dietary self-monitoring (Brazier et al., 1992; Carter et al., 2013; Turner-McGrievy et al., 2013; Ware, 2000) by reducing burden (e.g., having to look up foods consumed in a calorie book and record entries in a journal) (Burke et al., 2011; Glanz et al., 2006) while delivering real-time feedback on behaviors (Martin et al., 2009; Shaw et al., 2014). Despite technological advances, dietary self-monitoring can still be burdensome (Burke et al., 2009) and adherence can be low, typically decreasing over time (Burke et al., 2011; Turner-McGrievy et al., 2019a, b).

To date, no studies have defined what dietary self-monitoring burden is. Therefore, to inform this paper, we are defining burden based on definitions in other areas, including response burden (Rolstad et al., 2011), treatment burden (Alsadah et al., 2020), and user burden with computer technology (Suh et al., 2016). Definitions vary

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for these various types of burden, but one common thread is a high amount of effort (Rolstad et al., 2011), work (Alsadah et al., 2020), or mental burden (Suh et al., 2016) that is required by an individual. Based on the overlap in these prior definitions, we define burden for dietary self-monitoring as methods that are time-intensive and active (versus passive) and require regular effort from an individual to initiate, use, and record eating events.

Although the use of electronic methods of dietary self-monitoring is promising, there is still a “law of attrition” that occurs when using digital health tools, where users discontinue use of technology-based components (Eysenbach, 2005). Therefore, many studies looking to improve engagement with self-monitoring have looked to find ways to leverage technology to target sustained use via reducing burden (Sieverdes et al., 2013; Whitton, 2010). There is a tension between reducing user burden and forming new habits (e.g., regularly logging all meals) that support regular adherence to dietary self-monitoring. Most previous research has focused on reducing user burden and making self-monitoring easier for participants to accomplish (Dennison et al., 2013; Tang et al., 2015). Burden, however, may manifest itself as the need to frequently enter food items into an app, which may in turn help promote the formation of habits more easily than lower-burden approaches that may require less direct entry (e.g., wearable, photo-based, etc.) (Oulasvirta et al., 2012). Burden can be difficult to measure, with previous studies using time spent self-monitoring as a proxy measure (Harvey et al., 2019) or qualitative feedback from participants (Burke et al., 2009).

There are theoretical underpinnings that support the need to reduce burden for dietary self-monitoring. Targeting reductions in user burden can be informed by theories, such as user control theory (Eveland & Dunwoody, 2001) and cognitive load theory (Brunken et al., 2003; Paas et al., 2003). User control theory states that an increase in a variety of different ways to learn and access information adds to the control a user feels and therefore increases learning (Eveland & Dunwoody, 2001). Cognitive load theory states that the more cognitive burden, or mental effort, users feel when learning, the less able they will be to retain and act upon what they learned (Brunken et al., 2003; Paas et al., 2003). In addition, Self-Regulation Theory would suggest that the act of self-monitoring diet and receiving in-the-moment feedback on behaviors is a key component to self-regulation (Burke et al., 2011; Semper et al., 2016) and active forms of self-monitoring (e.g., regularly recording and being cognizant of food and beverage intake) would lead to greater information processing (Bagozzi et al., 2004; Hoyle, 2006) and greater attainment of goals (Harkin et al., 2016).

The focus of this paper is to review technology-based methods of dietary self-monitoring and efforts to reduce

the potential burden associated with each method. As compared to the standard paper or smartphone app-based approaches, innovative attempts have been made to lower burden using novel technology and approaches. Additionally, a case study is presented to examine the impact that two low-burden self-monitoring approaches have on habit formation. While many researchers are looking to reduce the burden associated with self-monitoring (Burke et al., 2012; Choe et al., 2017, 2015), this paper seeks to examine the tradeoff between low burden approaches and the formation of habits for regular dietary self-monitoring.

Standard Dietary Self-monitoring Methods

Dietary self-monitoring is a behavior that individuals complete each day, but does not require a high degree of accuracy, is mainly used for individual feedback, and is most often used to provide limited nutrient information, such as energy intake (Burke et al., 2011). Original methods of dietary self-monitoring traditionally relied on paper journals and books that contained information on the energy content of commonly consumed foods (Burke et al., 2011). With the advent of smartphones, mobile apps for dietary tracking began to be widely available (Ferrara et al., 2019). These apps could reduce user burden through the use of searchable databases, barcode scanning, and automatic calculations of calories and macronutrients (Chen et al., 2015). In addition, smartphones are ubiquitous (Pew Research Center, 2019) and one-third of mobile internet users report being online constantly (Perrin & Kumar, 2019), making it convenient to enter dietary information.

Even with these technological advances, traditional apps still require a certain degree of burden. Users must remember to log every eating occasion. In addition, users are encouraged to log foods as close to when they were consumed (Harvey et al., 2019), since proximal recording of dietary intake has been shown to be related to greater weight loss (Burke et al., 2008).

Regular dietary self-monitoring is an important component of successful weight loss. For example, visiting an online webpage to record dietary intake an average of 2–3 times per day was associated with greater likelihood of achieving clinically significant weight loss than recording on the webpage only once daily. Importantly, those who lost 10% or more were recording at least 20 days of the month (Harvey et al., 2019). Furthermore, comprehensiveness of food logging is strongly associated with sustained weight loss success (Peterson et al., 2014). Below details some of the technology that has been used to try to reduce burden (e.g., having to log every food and beverage item consumed each day) in standard diet tracking apps.

Self-monitoring Methods That Might Be Lower Burden

Wearable and Sensor-based Methods

While there are numerous types of wearable devices that can passively record and quantify physical activity (Sanders et al., 2016; Turner-McGrievy et al., 2019a, b), there are very limited commercially available wearable or sensor-based devices for tracking diet. Pressure-based sensors have begun to be explored for use in diet monitoring and includes approaches like embedding weight-sensors into placemats or tablecloths to detect the weight of food or eating movements (scrapping of a fork on the plate) (Vu et al., 2017). In addition, there have been sensors developed to detect auditory chewing sounds and the muscular contractions on the neck that occur during swallowing of food (Vu et al., 2017). Inertial approaches have also been developed to detect eating motions, such as using gyroscopes to detect rotations of the wrist (Vu et al., 2017). An example of this is the wrist-worn Bite Counter, where participants use the device during every eating occasion to track bites each day (Turner-McGrievy et al., 2017a, b). Physiological approaches that detect eating through movements of the vocal cords have also been developed (Vu et al., 2017). One wearable self-monitoring device currently commercially available, which may have potential for monitoring and modifying dietary intake, is a continuous wearable blood glucose monitoring device (Liao & Schembre, 2018). These devices can be used to train individuals in a weight loss program to correctly identify hunger states to determine when to eat (Jospe et al., 2017). While numerous approaches are being explored, wearable and sensor-based methods have not been evaluated on a large scale to demonstrate feasibility of use and effectiveness in improving self-regulation of dietary intake and few are currently commercially available.

Photo-based Methods

Photo-based approaches to tracking diet have mainly targeted dietary assessment, with the associated focus on obtaining accurate quantification of amounts and types of food and beverages consumed for nutrient analysis. These methods have included approaches such as the eButton or Remote Food Photography Method (Gemming et al., 2015). There have been a limited number of studies that have examined photo-based methods for dietary self-monitoring as a self-regulation tool (Kankanhalli et al., 2019) and few online apps for diet tracking are evidence-based (Hales et al., 2016a). Previous research has found that using crowdsourced ratings of the healthiness of foods consumed via posting photos may be an accurate way to provide diet feedback to an individual user (Turner-McGrievy et al., 2015). In addition, use of a

photo diet tracking app produced equivalent weight loss in a 6-month randomized intervention as a standard searchable food database app (Dunn et al., 2019). Photo-based apps for dietary self-monitoring are still very limited in the feedback they are able to provide so more work should be done to find ways that user food photos can be translated to usable information, such as calorie content (Hales et al., 2016b).

Ecological Momentary Assessment

Advances in mobile technology have led to the increasing usage of Ecological Momentary Assessment (EMA) to assess and understand the dynamics of dietary behaviors in everyday life. Usually, participants in EMA studies are asked to complete a brief dietary survey multiple times a day across the study period. These brief surveys often include simple open-ended questions, Likert-type/visual analog scales, or checklists to assess food and beverage intake on a given occasion. The brevity of the EMA dietary survey may be limited in providing rich dietary information as compared to other more comprehensive self-report methods (i.e., database apps). However, for dietary self-monitoring purposes, using EMA may be a promising approach to reduce participant burden, minimize recall bias, and enhance ecological validity (Shiffman et al., 2008).

To date, the event-contingent and the signal-contingent data collection strategies have been predominately implemented in smartphone-based EMA studies to assess individuals' dietary patterns (Mason et al., 2019; Maugeri & Barchitta, 2019; Schembre et al., 2018). The event-contingent strategy requires participants to proactively report their dietary consumption at (before or after) each eating occasion. Therefore, no pre-determined number of EMA self-reports are required to complete each day. The signal-contingent strategy, on the other hand, prompts the participants to provide dietary consumption each time when they receive a notification from the mobile device. The number of these notifications is usually fixed per day, and they are delivered based on a random (or semi-random) schedule. Thus, the random EMA self-reports collected from multiple occasions across the study period are considered representative of individuals' usual daily intake (Bruening et al., 2016; O'Connor et al., 2018). As both EMA sampling strategies conduct repeated assessments in real-time, real-life contexts, participants' cognitive strains and burden while recalling past dietary events may be reduced. The signal-contingent based strategy may also further minimize the burden associated with self-initiated efforts to record food and beverage consumption.

Some characteristics of EMA can also be burdensome. For example, participants may consider EMA to be intrusive and demanding as they are repeatedly interrupted throughout the day to provide dietary information (Wen et al., 2017). Emerging studies have leveraged various smartphone sensor data and applied novel algorithms to identify the optimal

time windows (those with a higher likelihood of responding) for delivering prompts to participants (Poppinga et al., 2014; Sarker et al., 2014). This developing technology provides opportunities to determine the minimum, but sufficient number of prompts to sustain participant engagement. Finally, most dietary EMA studies are not designed for self-monitoring as the primary goal, participants usually do not have access to historical data, nor do they receive feedback based on their inputs. Increased EMA data accessibility and transparency for participants can improve understanding of one's eating patterns, which, in turn, may enhance motivation for self-monitoring.

Case Study: the Relationship Between Burden and Habit Formation

In order to examine the impact that low-burden dietary self-monitoring approaches may have on habit formation (remembering to use the tracking device), data from two different remotely delivered weight loss interventions were used as a case study. The DIET mobile (Turner-McGrievy et al., 2017a, b) and 2SMART (Dunn et al., 2019) studies have been described elsewhere. Briefly, both studies were six-month remotely delivered weight loss interventions each testing two different dietary self-monitoring methods. Both groups received the same behavioral weight loss podcasts for 6 months. All participants provided written informed consent and the study was approved by the university IRB. Based on our definition of dietary self-monitoring burden, the present study looked at one higher burden method (a standard, traditional diet tracking app, which requires active and regular participation to initiate, use, and record eating events) versus two lower burden methods (a photo-tracking app and a wearable bite counter device, which are more passive and less time-intensive than entering every food into a searchable database). The DIET mobile study randomized participants to either self-monitor their diet with a wearable bite tracking device (Bite Counter group; $n = 39$) or a standard diet tracking app (Fat Secret app group; $n = 42$). The 2SMART study randomized participants to either an app that used photos to track diet (MealLogger app group; $n = 23$) or a standard diet tracking app (Fat Secret app group; $n = 23$). Main results of both the DIET mobile (Turner-McGrievy et al., 2017a, b) and 2SMART (Dunn et al., 2019) studies have been presented elsewhere. There was no difference in 6-month weight loss between the photo tracking approach and the more traditional diet tracking app in the 2SMART study, but in DIET mobile, Fat Secret app participants lost significantly more weight (-6.8 ± 0.8 kg) than the Bite Counter group (-3.0 ± 0.8 kg; $p < 0.001$).

After 6 weeks of using their assigned device, participants in both the DIET mobile and 2SMART study were asked questions to assess burden and habit formation. Because being unfamiliar with how to use something may lead to some usage burden, we also assessed novelty. To assess these constructs, participants were asked seven questions on a Likert scale (1 completely disagree to 7 completely agree) assessing likability of device, ease of use, novelty, remembering to use the device, understanding the feedback, and level of difficulty using the device. Analysis of variance was used to compare the mean scores for each question item among the three different dietary self-monitoring groups with Tukey's HSD test used to examine differences among the three groups (IBM SPSS Statistics for Windows, Version 26.0). Only those who completed the questionnaire at 6 weeks were included in the analysis (Bite Counter, $n = 31$, Fat Secret/Standard app, $n = 48$, MealLogger Photo App, $n = 21$). Table 1 shows the results from the questionnaire. There were no differences in the ratings among the three groups for likability, newness, understanding feedback, or helpfulness. While Bite Counter participants found their device to be more novel than Fat Secret participants, they also found their self-monitoring method harder to use than the Fat Secret participants. Of importance to the present study, both Bite Counter (5.0 ± 1.81) and MealLogger (4.0 ± 2.24) participants agreed with this statement more strongly than did the FatSecret (2.35 ± 1.79 ; $p < 0.05$ for both comparisons) participants: "I have found it difficult to remember to use my assigned diet tracking device on a regular basis" ($F = 19.176$, $p < 0.001$ for the omnibus test). This indicates that habit formation was stronger in the Standard App condition than the approaches that were aimed to be of lower burden. While the Bite Counter met our definition of low burden (more passive and less time-intensive than a standard diet tracking app), participants rated the device as more novel and harder to use than a standard app. It is possible that participants in that condition needed more than 6 weeks to become accustomed with the device for it to truly be a lower burden approach. However, all participants liked their device equally and reported their respective devices to be similarly helpful and innovative.

Strategies to Enhance Habit Formation

Going forward, it may be helpful to find ways to balance low burden approaches with habit formation (remembering to use the self-monitoring device) for the initiation of successful self-monitoring. In addition, future studies may wish to employ some of the potentially effective strategies detailed below, in order to ensure engagement with diet tracking.

Table 1 Feedback ratings from participants randomized to one of three different diet tracking methods

Item on feedback questionnaire*	Bite Counter <i>N</i> = 31	Fat secret/standard app <i>N</i> = 48	Meal logger/diet photo app <i>N</i> =21	<i>F</i> statistic for one-way ANOVA and <i>p</i> -value for differences among 3 groups
Likability: I have liked using my assigned diet-tracking device.	4.9 ± 1.76	5.54 ± 1.81	5.1 ± 2	<i>F</i> = 1.235; <i>p</i> = 0.30
Newness: I have found my assigned diet-tracking device to be very new and innovative.	5.16 ± 1.79	4.71 ± 1.86	5.33 ± 1.83	<i>F</i> = 1.073; <i>p</i> = 0.35
Novelty: I have found my diet tracking device to be very unusual and something I haven't done before.	5.87 ± 1.59 ^a	3.98 ± 2.24	5.19 ± 2.21	<i>F</i> = 8.453; <i>p</i> < 0.001
Habit formation: I have found it difficult to remember to use my assigned diet-tracking device on a regular basis.	5.0 ± 1.81 ^a	2.35 ± 1.79	4.0 ± 2.24 ^a	<i>F</i> = 19.176; <i>p</i> < 0.001
Ease of use: I found that using my assigned diet tracking device was very easy.	4.9 ± 1.92 ^a	5.83 ± 1.49	5.9 ± 1.48	<i>F</i> = 3.64; <i>p</i> = 0.03
Understanding feedback: I have found it difficult to understand what the feedback means on my assigned diet tracking device.	2.39 ± 1.87	2.56 ± 1.74	3.62 ± 2.18	<i>F</i> = 3.061; <i>p</i> = 0.05
Helpful: I feel that using my assigned diet tracking device has helped to ensure that I've been successful so far in losing weight.	4.58 ± 1.93	5.33 ± 1.85	4.48 ± 1.83	<i>F</i> = 2.273; <i>p</i> = 0.11

*Ratings on a scale of 1 (completely disagree) to 7 (completely agree)

^aSignificantly different from Fat Secret (*p* < 0.05)

Social Support and Social Gaming

Evidence shows that perceived social support is positively linked to dietary behaviors both directly and indirectly, including through dietary self-regulation (Anderson-Bill et al., 2011; Anderson et al., 2007; Lemstra et al., 2016; Riccio et al., 2019). To provide social support to promote dietary self-monitoring, various approaches have been examined, including capitalizing on existing social relationships (Gorin et al., 2005; Samuel-Hodge et al., 2017; West et al., 2016), providing support messages via automated tailored feedback or sharing feedback via social media groups (e.g., Twitter; Facebook) (Chung et al., 2017; Napolitano et al., 2013; Wang et al., 2012).

Notably, one emerging tactic for fostering social support for enhanced self-monitoring is social gaming (Hales et al., 2016a, b). This strategy is rooted in the broader concept known as gamification (Deterding et al., 2011; Johnson et al., 2016), which is characterized by the influence affordances (i.e., components and mechanics that structure games) have on psychological outcomes and experiences (e.g., autonomy; relatedness; competence; enjoyment), and in turn, motivation and behavioral outcomes (Koivisto & Hamari, 2019). Affordances may be expressed as points, leaderboards, rewards, avatars, or challenges among other elements (Koivisto & Hamari, 2019; Lewis et al., 2016). The application of

gamification has shown promise for improving engagement in health behavior interventions (Johnson et al., 2016; Koivisto & Hamari, 2019). However, few studies have harnessed gamification to directly target dietary self-monitoring, let alone social support for dietary self-monitoring (Hales et al., 2016a, b; Nour et al., 2019). One of these studies leveraged a social game in which users in a 3-month behavioral weight loss intervention could earn points for sending supportive messages to other users via a mobile app to encourage self-monitoring and goal achievement (Hales et al., 2016a, b). Points could then be exchanged for prizes (Hales et al., 2016a, b). Although these gamification elements did not result in an enhanced number of meals tracked over the final 3 days of the treatment relative to a group that received a non-gamified app, this area of research is in its infancy and warrants further exploration (Hales et al., 2016a, b).

Reminders/Notifications

The use of reminders or prompts to self-monitor can be an effective way to engage users in regular dietary self-monitoring. This can include approaches outside of the self-monitoring method (e.g., not embedded within an app), such as texting, calling, or emailing the individual (Greaney et al., 2012; Hutchesson et al., 2016) or can occur as within-app notifications (Hales et al., 2016a, b; Patel et al., 2019). Studies have examined both

automated reminders, such as those based on time of day (e.g., a reminder to self-monitor lunch around 12:30 pm) (Hales et al., 2016a, b) and the ability to have user-set reminders (Pagoto et al., 2018). Having reminder messages be goal-focused versus just a standard reminder to self-monitor, may also improve adherence (Liu & Willoughby, 2018). Future studies may wish to examine what types of prompts are most effective for enhancing regular self-monitoring, in addition to the timing of prompts and delivery methods.

Future Research Directions

More studies are needed to examine the ideal methods to self-monitor and understand the relationship between burden, habit formation, and engagement with dietary self-monitoring. Standard randomized controlled trials (RCTs) can continue to be used to evaluate and compare self-monitoring methods with varying levels of user burden; however, there is also a need for more innovative approaches to examine this complex behavior change technique. Standard RCTs may not be the optimal approach to gather the required information that the field lacks to optimize dietary self-monitoring. The Multiphase Optimization Strategy (MOST) is a framework from the engineering field that could be used to efficiently determine which dietary self-monitoring components are necessary to optimize a specific criterion, such as engagement or weight loss (Collins & Kugler, 2018). Although several different strategies that have potential to enhance habit formation and improve engagement with dietary self-monitoring were discussed, it is unclear whether all of these are necessary (e.g., is there unnecessary burden from multiple strategies) or what the optimal dose is (e.g., how many prompts/week). Breaking down specific strategies, whether commonly used or new innovative approaches, within dietary self-monitoring using this MOST framework could lead to better recommendations on the optimal way to self-monitor.

From a different perspective, it is also known that self-monitoring typically declines over time within a weight management program. It could be beneficial to identify the declines early on and switch an individual to another method of self-monitoring. This adaptive approach may be more effective than keeping users using the same methods over several months. Using a research design such as the Sequential Multiple Assignment Randomized Trial (SMART) could help to create an adaptive intervention for dietary self-monitoring aiming to sustain engagement and identify whether a burden threshold exists within an individual (Collins et al., 2007). For example, when self-monitoring begins to decline, it is unclear whether switching to a lower burden approach could maintain engagement, or whether it is best to add other strategies (e.g., prompting).

Conclusions

Dietary self-monitoring is an important component of successful weight management (Peterson et al., 2014). Participants in previous studies have indicated that dietary self-monitoring is burdensome (Burke et al., 2009) and mHealth technology has held promise as a way to reduce the burden of diet tracking (Burke et al., 2012). Both the DIET mobile and 2SMART studies indicate that lower burden self-monitoring approaches that align with our proposed definition of dietary self-monitoring burden may result in a lack of habit formation to regularly track diet. Building in strategies, such as prompting notifications or social gaming, could be useful to help remind individuals to use lower burden self-monitoring approaches. In addition, future studies may want to examine this burden and habit formation threshold through novel research designs in order to optimize future interventions using dietary self-monitoring. It appears that it will be important to balance burden and habit formation and to continue to find ways to make self-monitoring engaging and sustaining.

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Declarations

The authors complied with all ethical standards.

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