Predictors of Adherence to Diet App Use

Research-in-Progress

Meghna Saxena

Atreyi Kankanhalli

Yan Li

Abstract

Chronic diseases, such as obesity and diabetes, are leading causes of mortality globally. Prevention of such chronic diseases typically requires critical diet changes to improve diet quality. Studies suggest that consistent diet-tracking can lead to improvement in diet quality. In this regard, smartphones have enabled diet-tracking through numerous apps for healthy eating and diet monitoring. However, these apps often suffer from high non-adherence, which prevents them from providing potential benefits to the users. Thus motivated, this work aims to model and identify predictors of adherence to diet app use, and particularly, the role of coaching. Preliminary analysis was done using panel data obtained from a diet app, and shows that coaching advice in addition to demographic variables can predict adherence. This study thus provides initial findings to help understand how to improve adherence to diet apps, as an enabler for improving diet quality and health outcomes.

Keywords: Diet, adherence, smartphone apps, predictors, coaching

Introduction

Chronic diseases such as obesity, diabetes, and other cardiovascular diseases are becoming major epidemics (Lavie et al. 2016) and are leading causes of morbidity and mortality globally (Abubakar et al. 2015). In developed countries like Singapore, chronic diseases, especially diabetes, are a significant cause of illness and fatality (Ong 2017). In-fact, in his 2017 National Day Rally address, Prime Minister Lee Hsien Loong referred to diabetes as one of three key long-term issues for Singapore (Abu Baker 2017). The health burden of diabetes is extensive as it is the leading cause of kidney failure, adult blindness, and amputations (WHO 2016). Among the causes, poor diet is a primary contributor to diabetes as well as other chronic diseases (Micha et al. 2017). Hence, prevention of such chronic diseases requires crucial diet improvements.

Many behavior change techniques (BCTs) have been employed in interventions aimed at improving diet choices and weight loss (Abraham and Michie 2008). Some of the BCTs recommended include self-monitoring (Burke et al. 2011), feedback (Chiasson et al. 2015), goal-setting, and social-support (Lehto and Oinas-Kukkonen 2015). Traditional diet monitoring methods involve recording food diaries, calorie logs, and goal-review all using paper journals (Helsel et al. 2007). However, food and calorie details are difficult to remember and logging these details can be time-consuming (Thompson et al. 2010). Similarly, manually checking progress against goals is challenging. Further, providing feedback and social-support through in-person counseling and group sessions is resource-intensive (Coughlin et al. 2015).

In this regard, smartphones have facilitated diet monitoring considerably through numerous apps for healthy eating and diet monitoring available in both Android as well as iOS app stores (Bardus et al. 2016). These apps help users record their food intake (Arens-Volland et al. 2015) automatically by capturing photos of food using smartphone cameras or manually by entering logs on the app. Further, these apps offer a way to gain feedback, via automatic, personal data-based insights (e.g. plots or graphs of users' progress on the app) or through researchers and health coaches by means of app messages. Moreover, interventions delivered through smartphone apps can reach a large number of people at little cost due to the widespread adoption of mobile phones. This makes smartphone apps for diet an appropriate tool for providing personalized diet interventions.

However, adherence to app use and interventions is seen as key to making desired diet changes. As per the literature, adherence can be defined in terms of "intended use" or "following recommendations to gain maximum benefit" (Sieverink et al. 2017). While, adherence to diet app use has been found beneficial (Peterson et al. 2014), the extent of diet app use often declines over time (Burke et al. 2011) and these apps suffer from high attrition (Mata et al. 2017; Webber et al. 2010). Indeed, some observational studies have reported adherence rates as low as 2.58% (Helander et al. 2014). To improve adherence to diet apps, we need to uncover the factors that predict adherence.

Thus motivated, this work aims to model (using behavioral theories) and identify predictors of adherence to diet app use. We particularly examine the role of coaching, which is not well understood in the context of diet app use (Franco et al. 2016). Preliminary model estimation was done using panel data obtained for a diet app, and shows that coaching advice in addition to demographic variables can predict adherence. This study thus provides initial findings to help understand how to improve adherence to diet apps, as an enabler for improving diet quality and health outcomes.

This paper proceeds as follows. In the next section, we review the relevant literature on definition and predictors of adherence to diet apps, and the theories used. Subsequently, we present our estimation model, research methodology, and study context. Finally, we report our results and discuss our initial findings and contributions. In our future research, we propose to study the relationship between adherence to diet app use and health outcomes (diet quality and weight loss), as an important step in understanding how technology can support health improvements in users.

Conceptual Background

Definition and Measures of Adherence

As per the World Health Organization (WHO), adherence has been defined as "the extent to which a person's behavior… corresponds with agreed recommendations from a health care provider" (WHO 2003). This was revised to cater to eHealth technologies as "the degree to which individuals experience the content of the Internet intervention" (Christensen et al. 2009) and as "the degree to which the user followed the program as it was designed" (Donkin et al. 2011). More recently, researchers have defined adherence as "intended use" or "following recommendations to gain maximum benefit" (Sieverink et al. 2017).

While low-adherence could be a generic problem for most health apps, users' difficulty and effort in tracking each meal poses a specific challenge for adherence to diet app use. Prior studies have measured adherence to diet app use in varied ways, e.g., the total number of app entries throughout the trial (Liu and Willoughby 2018), total number of days diet logged on app (Carter et al. 2017), and percentage of days with prescribed minimum calorie intake logged per day (Spring et al. 2017). These studies have employed frequency of use as measures of app adherence, while adherence to interventions or dietary guidelines have been assessed by the extent of logging on the app (Peterson et al. 2014). Frequency of use has been assessed by the total number of entries on the app within a specific duration (e.g., days, weeks, months), while extent of use has been measured by the detail or thoroughness with which the user records entries (e.g., calories, number of meals in a day, nutritional values). Consistency is measured by the total number of days that users log their diet without a break. Consolidating these different measures, 4 indicators of adherence were identified i.e., frequency, consistency, detail or extent, and intention to use (Brindal et al. 2018; Lieffers et al. 2018; Peterson et al. 2014). The most commonly used measures of adherence were found to be frequency of diet-tracking, followed by the combination of frequency and extent of diet tracking.

Predictors of Adherence

Adherence to using diet apps can be predicted by several factors, such as intrinsic motivation (Elavsky 2017), diet perception (Goh et al. 2015), reminders and peer counseling (Abdulrahman et al. 2017). Further, demographic variables like age (Comulada et al., 2018), gender (Goh et al., 2015), and education (Abril 2016) have also been found to be correlated with adherent app use. However, there is a lack of research that analyzes the factors predicting adherence to using diet apps longitudinally using panel data. Moreover, potential predictors such as personalized dietitian feedback or coaching through smartphone technology have not been studied with regard to their influence on user's adherence to diet app use (Franco et al. 2016). Lastly, there is a lack of theory-based prediction of adherence. With this study, we aim to provide initial evidence to address this research gap on the topic of adherence to a new technology platform, and contribute to a broader IS literature on technology acceptance and usage.

Theories Used

The theoretical orientation of this study is informed by the information-motivation-behavioral skills (IMB) model (Fisher et al. 2006) and self-regulatory theory (Bandura 1998). Both models describe processes of behavior change mediated through goal attainment and skill mastery, and both models acknowledge the central role that self-efficacy plays in sustained behavior change. The IMB model hypothesizes that cognitive and behavioral skills are a prerequisite for any health behavior change, like improving diet quality. However, skills are the product of information that is relevant to health problems and personal and social support for activation to change behavior. Thus, information interacts with activation to enhance self-efficacy and build skill mastery to facilitate sustained behavior change.

As diet apps typically have coaching and feedback components, these components could boost the positive reinforcing relationship between self-monitoring and feedback. Human coaches that communicate with users through the app can enhance activation by providing social support, helping to develop specific plans of action, helping with problem solving to avoid or mitigate barriers to behavior change, and enhancing engagement with the app by helping to interpret the individuals 'log data and using it to monitor progress.

The theory of self-regulation also informs our study. In self-regulation, individuals participate in self-directed behaviors. These self-directed behaviors are hypothesized to be managed through a dynamic feedback loop in which individuals' self-monitoring and feedback about their past behavior are integrated into their activation to change future behaviors (Vohs and Baumeister 2004). The self-monitoring and feedback loop in diet apps can act on self-efficacy via 2 pathways i.e., influencing users' activation to adhere to use, and providing data for coaches to customize motivational messages. Thus, both theories suggest a positive role of coaching in enhancing adherence and health outcomes and explain the underlying mechanisms for this role.

Methodology and Model

Study Context

This work employs user data obtained from a diet app, as part of an agreement between the app developer and our university. The app acts as a "mobile dietitian" and gives users customised advice on how to prevent or control diabetes and other chronic diseases. Users upload photos of meals, input glucose levels, attend interactive online lessons, and receive personal coaching from the app's in-house dietitians on gradual lifestyle changes. The dietitians provide a star rating (from 1-5) of users' meals, as well as counsel users on how to improve their diet.

Anonymized data of 1448 users who signed up for the app between July, 2015 and April, 2018 was provided. The data entry period of users went from 1 week to 101 weeks. The data was spread across 4 separate files i.e., baseline demographic data, meal entries, weight entries, comments data and glucose entries. Glucose data was not analysed as the data was present only for 120 users. Users recording data on the app for less than 2 weeks were excluded. This left us with a sample of 644 users (5129 records) for our final analysis.

Model Variables and Descriptives

The most widely used adherence measures identified by our literature review were extracted from the data to assess adherence i.e., frequency of diet tracking (Days_per_week) and frequency of extent of diet tracking (Meal_frequency). These represented the two dependent variables for our study. The number of comments delivered by coaches in each week for each user relative to their diet entries (Comments_by_coach) was extracted from the comments file and treated as the independent variable. Demographic variables of each user i.e., age, gender, BMI, objective, and ethnicity were extracted as control variables. These variables were included in the model owing to their potential to predict adherence as described earlier. The variables and correlations are shown in Tables 1 and 2 respectively.

Table 1. Model Variables

Measure	Variable	Description
Adherence (Dependent Variable)	Days_per_week	Frequency Total Days in week at-least 1 meal logged
Adherence (Dependent Variable)	Meal_frequency	Frequency of extent Meals logged/Days meal logged/per week
Independent Variable	Comments_by_coach	Number of comments given by health coach regarding the meal photos uploaded on app/per week
Control	Age	Specified by user at registration
Control	BMI	Calculated from onboarding weight and height specified by user at registration
Control	Gender	Specified by user at registration 1: Male; 0: Female
Control	Objective	User's objective to join the app as specified at registration: Pre-diabetes, T2Diabetes, High blood pressure, High cholesterol, None: Stay healthy (baseline)
Control	Ethnicity: Ethnicity_Chinese, Ethnicity_Malay, Ethnicity_Indian	Specified by user at registration Converted to binary dummies representing Chinese, Indian or Malay

Table 2. Descriptives and Correlations

	1	2	3	4	5	6	7
1. Gender	-						
2. Age	0.23**	-					
3. BMI	0.04	0.15**	-				
4. Meal_frequency	-0.07	0.12**	0.07	-			
5. Days_per_week	0.05	0.17***	0.12***	0.50***	-		
6. Comments_lagged	-0.09	-0.19**	0.01	0.08	0.01	-	
7. Days_per_week_lagged	0.04	0.15**	0.11**	0.44***	0.64***	0.08	-
8. Meal_freq_lagged	-0.08	0.12**	0.06	0.65***	0.42***	0.16***	0.50***
Mean	53.85% female	42.23	28.43	1.91	3.85	15.23	-
Std. Deviation		17.35	5.94	1.32	2.19	20.12	-
Range		18-78	15.2-53.4	1-10/day	1-7/week	0-203/week	-
Note: * p<0.05; ** p<0.01; *** p<0.001							

Estimation Model

Our proposed model for adherence to diet app use based on the chosen variables is:

$$Adherence_{i,t} = \beta_1 Comments\_by\_coach_{i,t-1} + \beta_2 Adherence_{i,t-1} + \alpha_1 BMI_i + \alpha_2 Age_i + \alpha_3 Gender_i + \alpha_4 Pre\text{-}diabetes_i + \alpha_5 T2Diabetes_i + \alpha_6 High\_blood\_pressure_i + \alpha_7 High\_cholesterol_i + \alpha_8 Ethnicity\_Chinese_i + \alpha_9 Ethnicity\_Indian_i + \alpha_{10} Ethnicity\_Malay_i + \epsilon_{i,}$$

where, i represents each user; t represents each week of entry; t-1 represents lagged variables;
Adherence was assessed by two separate dependent variables:
DV1 – *Days_per_week*, DV2 – *Meal_frequency* (see Table 1)
Both adherence outcomes estimated by the equation are presented in the Results section. The Hausmann Test was applied to determine whether to run the fixed effects or random effects model.

Results

We performed a fixed effects regression for estimation of both adherence outcomes (p value <0.05 in the Hausmann Test). Table 3 shows the panel regression results for both DVs (see columns 1 and 3. Both DVs are significantly and positively influenced by Comments_by_coach and the corresponding lagged DVs. The model F-statistic is over critical value (Fcritical = 2.99 for df 2, 4482) and p-statistic < 0.05 indicating that the dependent variables are significantly influenced by the independent variable. It is to be noted that Rsquare values are usually low for panel data as Rsquare is determined for time series as opposed to cross-sectional data (Wooldridge 2011).

Table 3. Results of Model Estimation

	DV1: Days_per_week		DV2: Meal_frequency	
	Column (1)	Column (2)	Column (3)	Column (4)
	Fixed Effects	Random Effects	Fixed Effects	Random Effects
	Coefficients (Std. Error)	Coefficients (Std. Error)	Coefficients (Std. Error)	Coefficients (Std. Error)
Intercept (Error)	-	0.266 (0.191)	-	0.390*** (0.098)
Comments_by_coach (lagged)	0.005*** (0.001)	0.008*** (0.001)	0.004*** (0.001)	0.010*** (0.001)
Meal_frequency (lagged)	0.099*** (0.017)	0.508*** (0.014)	-	-
Days_per_week (lagged)	-	-	0.382*** (0.016)	0.601*** (0.014)
BMI	-	0.031*** (0.005)	-	0.004 (0.002)
Age	-	0.008*** (0.002)	-	0.003** (0.001)
Gender	-	0.059 (0.051)	-	-0.072** (0.026)
Pre-diabetes	-	0.038 (0.185)	-	-0.053 (0.094)
T2Diabetes	-	0.170* (0.079)	-	0.008 (0.040)
High_blood_pressure	-	-0.012 (0.101)	-	0.059 (0.052)
High_cholesterol	-	-0.034 (0.093)	-	-0.089 ~ (0.047)
Ethnicity_Chinese	-	0.198** (0.071)	-	-0.033 (0.036)
Ethnicity_Indian	-	-0.111 (0.106)	-	-0.081 (0.054)
Ethnicity_Malay	-	-0.029 (0.089)	-	-0.039 (0.046)
R^2	0.025	0.38	0.21	0.55
F-statistic	58.55	261.88	587.55	528.30
P-value	< 2.22e-16	< 2.22e-16	< 2.22e-16	< 2.22e-16
Hausmann Test	p-value < 2.2e-16 Random Effects Inconsistent		p-value < 2.2e-16 Random Effects Inconsistent	
Note: ~ p<0.1; * p<0.05; ** p<0.01; *** p<0.001				

The random effects models were run for checking robustness and show similar results (columns 2 and 4 of Table 3).

Discussion and Initial Contributions

This study used panel data from 644 users of a diet app and successfully developed a fixed effects model for estimation of adherence to app use, accounting for both individual and time-fixed effects. We found that adherence is positively influenced by the number of comments given by the coach and the user's frequency of logging (number of days as well as number of meals) in the previous week. These results suggest that smartphone app delivered coaching feedback can increase adherence to app use.

Contributions to Research and Practice

As mentioned earlier, adherence to diet app use has typically been assessed using cross-sectional data with group effects, which limits the applicability of prior results. This study used panel data and a fixed effects model for estimation of adherence to address this limitation. Moreover, prior research fails to examine the effect of personalized dietitian feedback with smartphone technology on user's adherence to diet app use (Franco et al. 2016). This study contributes to the literature by finding that dietician feedback indeed increases user adherence to diet app use. Additionally, the sample considered is sufficiently large and representative, so the analyses could provide a general idea about user behavior.

Based on the findings of this study, the number of comments by health coaches should be increased as they positively influence adherence to diet app use. This research may also benefit clinicians as these results provide support for connecting with patients through app based interactions outside of a formal nutrition counseling sessions that are more resource intensive.

Limitations and Future Work Plan

A limitation of this study is that the analysis is limited to the data that users log onto the app, which could be prone to omissions and errors. More efficient diet logging methods will be considered in future to address this issue. This study is also limited by the app used for data collection and analysis. Drawbacks of the app include lack of features for implementing BCTs like goal-setting, and rewards (Schoeppe et al. 2016). Also, the coaching feedback given through the app is manual. Thus, we will make use of data from diet apps that include the missing features and automated feedback in future. Additionally, we will extend the scope of the research to examine the outcomes of adherence to diet app use, such as diet quality and weight loss. Furthermore, the endogeneity issue is not addressed, especially for the relationship between the number of comments and the frequency of meals logged. Thus, we do not claim causality, for which randomized experiments should be conducted in future. Last but not least, it would also be valuable in future to extract qualitative information from the coaches' comments by leveraging natural language processing (NLP) techniques to complement the quantitative variable of number of comments in predicting adherence.

References

Abdulrahman, S.A., Rampal, L., Ibrahim, F., Radhakrishnan, A.P., Shahar, H.K., and Othman, N. 2017. "Mobile Phone Reminders and Peer Counseling Improve Adherence and Treatment Outcomes of Patients on ART in Malaysia: A Randomized Clinical Trial," *PloS one* (12:5), e0177698.

Abraham, C., and Michie, S. 2008. "A Taxonomy of Behavior Change Techniques Used in Interventions," *Health Psychology* (27:3), pp. 379.

Abril, E.P. 2016. "Tracking Myself: Assessing the Contribution of Mobile Technologies for Self-Trackers of Weight, Diet, or Exercise," *Journal of Health Communication* (21:6), pp. 638–646.

Abubakar, I.I., Tillmann, T., and Banerjee, A. 2015. "Global, Regional, and National Age-Sex Specific All-Cause and Cause-Specific Mortality for 240 Causes of Death, 1990-2013: A Systematic Analysis for the Global Burden of Disease Study 2013," *Lancet* (385:9963), pp. 117-171.

Arens-Volland, A.G., Spassova, L., and Bohn, T. 2015. "Promising Approaches of Computer-Supported Dietary Assessment and Management - Current Research Status and Available Applications," *International Journal of Medical Informatics* (84:12), pp. 997–1008.

Bandura, A. 1998. "Health Promotion from the Perspective of Social Cognitive Theory," *Psychology and Health* (13:4), pp. 623-649.

Bardus, M., van Beurden, S.B., Smith, J.R., and Abraham, M. 2016. "A Review and Content Analysis of Engagement, Functionality, Aesthetics, Information Quality, and Change Techniques in the Most Popular Commercial Apps for Weight Management," *International Journal of Behavioral Nutrition and Physical Activity*, 13.

Brindal, E., Hendrie, G.A., Freyne, J., and Noakes, M. 2018. "Incorporating a Static versus Supportive Mobile Phone App into a Partial Meal Replacement Program with Face-to-Face Support: Randomized Controlled Trial," *JMIR mHealth and uHealth* (6:4), e41.

Burke, L.E., Conroy, M.B., Sereika, S.M., Elci, O.U., Styn, M.A., Acharya, S.D., … Glanz, K. 2011. "The Effect of Electronic Self-Monitoring on Weight Loss and Dietary Intake: A Randomized Behavioral Weight Loss Trial," *Obesity* (19:2), pp. 338–344.

Carter, M.C., Burley, V.J., and Cade, J.E. 2017. "Weight Loss Associated with Different Patterns of Self-Monitoring Using the Mobile Phone App My Meal Mate," *Journal of Medical Internet Research* (19:2).

Chiasson, M., Kelley, H., and Downey, A. 2015. "Understanding Task-Performance Chain Feed-Forward and Feedback Relationships in E-health," Special Issue: HCI in Health and Wellness. *AIS Transactions on Human-Computer Interaction* (7:3), pp. 167–190.

Christensen, H., Griffiths, K.M., and Farrer, L. 2009. "Adherence in Internet Interventions for Anxiety and Depression," *Journal of Medical Internet Research* (11:2), e13.

Comulada, W.S., Swendeman, D., Koussa, M.K., Mindry, D., Medich, M., Estrin, D., … Ramanathan, N. 2018. "Adherence to Self-Monitoring Healthy Lifestyle Behaviours through Mobile Phone-based Ecological Momentary Assessments and Photographic Food Records over 6 Months in Mostly Ethnic Minority Mothers," *Public Health Nutrition* (21:4), pp. 679–688.

Coughlin, S.S., Whitehead, M., Sheats, J.Q., Mastromonico, J., Hardy, D., and Smith, S.A. 2015. "Smartphone Applications for Promoting Healthy Diet and Nutrition: A Literature Review," *Jacobs Journal of Food and Nutrition* (2:3), pp. 21.

Donkin, L., Christensen, H., Naismith, S.L., Neal, B., Hickie, I.B., and Glozier, N. 2011. "A Systematic Review of the Impact of Adherence on the Effectiveness of E-Therapies," *Journal of Medical Internet Research* (13:3), e52.

Elavsky, S., Smahel, D., and Machackova, H. 2017. "Who are Mobile App Users from Healthy Lifestyle Websites? Analysis of Patterns of App Use and User Characteristics," *Translational Behavioral Medicine* (7:4), pp. 891–901.

Fisher, J.D., Fisher, W.A., Amico, K.R., and Harman, J.J. 2006. "An Information-Motivation-Behavioral Skills Model of Adherence to Antiretroviral Therapy," *Health Psychology* (25:4), pp. 462.

Franco, R.Z., Fallaize, R., Lovegrove, J.A., and Hwang, F. 2016. "Popular Nutrition-Related Mobile Apps: A Feature Assessment," *JMIR mHealth and uHealth* (4:3), e85.

Goh, G., Tan, N.C., Malhotra, R., Padmanabhan, U., Barbier, S., Allen, J.C.J., and Ostbye, T. 2015. "Short-Term Trajectories of Use of a Caloric-Monitoring Mobile Phone App Among Patients with Type 2 Diabetes Mellitus in a Primary Care Setting," *Journal of Medical Internet Research* (17:2), e33.

Helander, E., Kaipainen, K., Korhonen, I., Wansink, B. 2014. "Factors Related to Sustained Use of a Free Mobile App for Dietary Self-Monitoring with Photography and Peer Feedback: Retrospective Cohort Study," *Journal of Medical Internet Research* (16:4), e109.

Helsel, D.L., Jakicic, J.M., and Otto, A.D. 2007. "Comparison of Techniques for Self-Monitoring Eating and Exercise Behaviors on Weight Loss in a Correspondence-Based Intervention," *Journal of the American Dietetic Association* (107:10), pp. 1807–1810.

Abu Baker, J. 2017, August 20. "National Day Rally: 1 in 9 Singaporeans has Diabetes; Problem 'very serious', says PM Lee," https://www.channelnewsasia.com/news/topics/nd2017/national-day-rally-1-in-9-singaporeans-has-diabetes-problem-very-9140176

Lavie, C.J., De Schutter, A., Parto, P., Jahangir, E., Kokkinos, P., Ortega, F. B., … Milani, R.V. 2016. "Obesity and Prevalence of Cardiovascular Diseases and Prognosis-The Obesity Paradox Updated," *Progress in Cardiovascular Diseases* (58:5), pp. 537-547.

Lehto, T., and Oinas-Kukkonen, H. 2015. "Examining the Persuasive Potential of Web-based Health Behavior Change Support Systems," Special Issue: HCI in Health and Wellness. *AIS Transactions on Human-Computer Interaction* (7:3), pp. 126–140.

Lieffers, J.R.L., Arocha, J.F., Grindrod, K., and Hanning, R.M. 2018. "Experiences and Perceptions of Adults Accessing Publicly Available Nutrition Behavior-Change Mobile Apps for Weight Management," *Journal of the Academy of Nutrition and Dietetics* (118:2), 229–239.e3.

Liu, S., and Willoughby, J.F. 2018. "Do Fitness Apps Need Text Reminders? An Experiment Testing Goal-Setting Text Message Reminders to Promote Self-Monitoring," *Journal of Health Communication* (23:4), pp. 379–386.

Mata, F., Treadway, M., Kwok, A., Truby, H., Yücel, M., Stout, J.C., and Verdejo-Garcia, A. 2017. "Reduced Willingness to Expend Effort for Reward in Obesity: Link to Adherence to a 3-Month Weight Loss Intervention," *Obesity* (25:10), pp. 1676–1681.

Micha, R., Shulkin, M.L., Peñalvo, J.L., Khatibzadeh, S., Singh, G.M., Rao, M., … Mozaffarian, D. 2017. "Etiologic Effects and Optimal Intakes of Foods and Nutrients for Risk of Cardiovascular Diseases and Diabetes: Systematic Reviews and Meta-Analyses from the Nutrition and Chronic Diseases Expert Group (NutriCoDE)," *PloS One* (12:4).

Ong, Y.Y. 2017. "Burden of Diabetes: A Refocus," *Proceedings of Singapore Healthcare* (26:4), pp. 209–210.

Peterson, N.D., Middleton, K.R., Nackers, L.M., Medina, K.E., Milsom, V.A., and Perri, M.G. 2014. "Dietary Self-Monitoring and Long-Term Success with Weight Management," *Obesity* (22:9), pp. 1962–1967.

Schoeppe, S., Alley, S., Van Lippevelde, W., Bray, N.A., Williams, S.L., Duncan, M.J., and Vandelanotte, C. 2016. "Efficacy of Interventions that Use Apps to Improve Diet, Physical Activity and Sedentary Behaviour: A Systematic Review," *International Journal of Behavioral Nutrition and Physical Activity* (13:1), pp. 127.

Sieverink, F., Kelders, S.M., and Gemert-Pijnen, V. 2017. "Clarifying the Concept of Adherence To E-Health Technology: Systematic Review on When Usage Becomes Adherence,' *Journal of Medical Internet Research* (19:12), e402.

Spring, B., Pellegrini, C.A., Pfammatter, A., Duncan, J.M., Pictor, A., McFadden, H.G., … Hedeker, D. 2017. "Effects of an Abbreviated Obesity Intervention Supported by Mobile Technology: The ENGAGED Randomized Clinical Trial," *Obesity* (25:7), pp. 1191–1198.

Thompson, F.E., Subar, A.F., Loria, C.M., Reedy, J.L., and Baranowski, T. 2010. "Need for Technological Innovation in Dietary Assessment," *Journal of the American Dietetic Association* (110:1), pp. 48–51.

Vohs, K.D., Baumeister, R.F. 2004. "Self-Regulation of Action and Affect." in *Handbook of Self-Regulation: Research, Theory, and Applications*. New York, NY: Guilford Press, pp. 3-24.

Webber, K.H., Tate, D.F., Ward, D.S., and Bowling, J.M. 2010. "Motivation and its Relationship to Adherence to Self-monitoring and Weight Loss in a 16-week Internet Behavioral Weight Loss Intervention," *Journal of Nutrition Education and Behavior* (42:3), pp. 161–167.

WHO. 2003. Adherence to long-term therapies: Evidence for action. http://www.who.int/chp/knowledge/publications/adherence_full_report.pdf

Wooldridge, J.M. 2011. *Econometric Analysis of Cross Section and Panel Data*. MIT Press, Cambridge: MA.

WHO. 2016. Global Report on Diabetes. https://www.who.int/diabetes/global-report/en/