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A PILOT STUDY OF THE EFFECTIVENESS AND USABILITY OF THE
MYENERGYBALANCE IPHONE APP AND WEBSITE

A Thesis Presented

by

Joanna Graff

to

The Faculty of the Graduate College

of

The University of Vermont

In Partial Fulfillment of the Requirements
For the Degree of Master of Science
Specializing in Nutrition and Food Sciences

October, 2016

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Thesis Examination Committee:

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ABSTRACT

The powerful technical capabilities of smartphones offer unprecedented opportunities for collecting dietary information. We have developed an enhanced smartphone application called MyEnergyBalance, which permits imaged-based self-monitoring of all foods consumed, and links to a convenient and user-friendly web-based dietary assessment tool. The primary objective of this pilot study was to determine if the MyEnergyBalance app (with use of images) in combination of the associated website improves dietary recall compared to diet analysis on the MyEnergyBalance website alone. We also generated preliminary data on the usability of the MyEnergyBalance iPhone app and website. This pilot study was a crossover study design of healthy, college students. Participants were randomly assigned to two groups. Both groups consumed their normal diet for the first day with one group recording their food intake with image functions of the MyEnergyBalance app, while the other group did not use the app. On the second day, all participants logged into the MyEnergyBalance website to record their food intake from the previous day; one group using the images from the app to assist in recalling what they ate, while the other group recalled what they ate from memory. The diet analysis results were compared to those obtained using the ASA24 website. The groups were then crossed over to the opposite vs no-image assisted recalls. Ten participants (seven females and three males) aged 20 to 22 years completed this study. The average BMI of all participants was 23.12 kg/m² (ranging from 18.95 to 32.28 kg/m²). There was no statistically significant differences in the estimates of the energy intake between the MyEnergyBalance app and website compared to ASA24. The SUS mean score for the MyEnergyBalance app and website was 86 and 69.5, respectively. A strong, negative correlation was found between the system usability scale scores and the absolute differences in energy intake of the MyEnergyBalance app and ASA24. Although we were not able to demonstrate a significant benefit of the images from the iPhone app at improving food recall (perhaps due to the small study sample size), we were able to demonstrate a high usability score for the iPhone app, average usability score for the website, and a significant correlation between subjects' usability scores and relative accuracy of the subjects' food recall using the images from the iPhone app. A future study with a larger sample size will hopefully provide more information on the efficacy of image-based food recalls.

DEDICATION

This thesis is dedicated to my wife Veena, my partner, best friend, my inspiration and most important, someone who believed in me. This thesis would simply not have happen without her unconditional love and support.

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Most importantly, I would like to thank my advisor, Professor Stephen Pintauro for guiding and supporting me over the years. You have truly set an example of excellence as a researcher, instructor, mentor, and role model.

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REVIEW OF THE LITERATURE

Introduction

Obesity has reached epidemic proportions in the United States and has become one of our nation's most pressing public health concerns. The prevalence of overweight and obesity has increased significantly among US adults in recent years, with more than two-thirds of the adult population in the US considered overweight or obese as of 2012.¹ If the current trends in the prevalence of overweight and obesity continue, the projected rate of obesity will increase to more than half for all US adult population by 2030, with an estimated increase of 45-52 percent for woman and 50-51 percent for men.^{2,3} Over the past 30 years, childhood obesity rates in the US have tripled, with more than one-third of all children and adolescents in the US considered overweight or obese as of 2012.^{1,4} In 2012, 31.8 percent of children and adolescents in the US were either overweight or obese, and 16.9 percent were obese.¹ There is strong evidence that childhood obesity creates adverse consequences on health, which may be immediate or may become fully apparent in adult life. Several studies have shown the association of childhood obesity with an increased likelihood of adult obesity, and the related effects on health and well-being.^{5,6 7-9} In particular, overweight and obesity during adolescence were significantly associated with insulin resistance, dyslipidemia, and elevated blood pressure in young adults.¹⁰

Obesity is a complex condition resulting from an imbalance between energy intake and energy expenditure.¹¹ According to the CDC, the primary contributors to the current high rates of overweight and obesity among adults and children in the US include various genetic, environmental, and behavioral factors, such as excessive overall caloric intake, excessive intake of high energy and high fat foods, and insufficient physical activity. The consequences of obesity include deleterious effects on overall health, and are associated with an increased risk of morbidity from hypertension, cancer, coronary heart disease, and type II diabetes.^{12,13} The effect of obesity has also been associated with a higher prevalence of disability¹⁴⁻¹⁶ and increased mortality¹⁷⁻²⁴ among US adults. Children diagnosed with type II diabetes are also at risk of obesity-related complications, including hypertension, nonalcoholic fatty liver disease, and metabolic syndrome.²⁵ The prevalence of type II diabetes among children and adolescents has significantly increased between 2001 and 2009, with a relative increase of 35 percent among youth aged 10-19.²⁶ By 2050, projections suggest that the number of individuals diagnosed with type II diabetes will increase by a staggering 49 percent in youth,²⁷ and by 21 percent in adults if incidence rates remain the same.²⁸

The economic burden of obesity-related chronic diseases has a significant impact on the US health care system, with an estimated cost of \$147 billion in 2008, most of which is associated with the four diseases listed above.²⁹ Health care costs associated with overweight and obesity increased substantially over

the years,²⁹⁻³² and are expected to rise significantly if current trends continue. Health care spending on obese individuals has been estimated to be 37 percent higher than those with normal weight,³³ and it was estimated to account for 5.5-7.0 percent of the US total health care expenditures.³⁴ Also, the increasing prevalence of obesity and increased spending on obese individuals has accounted for 27 percent of the growth in US healthcare spending between 1987 and 2001.³³ By 2030, the total health care costs attributed to obesity will double every decade, accounting for 16-18 percent of total US health care cost.³⁵ These implications suggest that immediate efforts to prevent the rising prevalence and cost of obesity must be addressed.

Overview of Treatment Options

A number of weight management interventions for overweight and obese individuals are available, including surgical procedures, pharmacologic, dietary, modifying physical activity patterns, behavior therapy, as well as combinations of these interventions.^{36,37} Proper assessment of obesity through a determination of BMI, waist circumference, co-morbidities, and other risk factors should be performed before implementing any weight management intervention.³⁷

Surgical interventions are recommended for individuals with clinically severe obesity with a BMI of 40 or greater, or a BMI of 35 or greater with comorbidities. However, this treatment option should only be performed on individuals for whom other less intensive interventions have not been successful.

³⁷ There are two most commonly performed bariatric surgeries, laparoscopic adjustable banding (AGB) and Roux-en-Y gastric bypass (RYGB). These types of surgeries classify into two different categories: restrictive (AGB) and restrictive-malabsorptive procedures (RYGB). Restrictive surgeries purely restrict gastric volume and produce a feeling of fullness with decreased food intake. The restrictive-malabsorptive surgeries not only decrease the volume of food intake the stomach can hold, but they also alter digestion and absorption by bypassing part of the stomach and a portion of the intestine.³⁸ Overall the outcomes of bariatric surgeries result in greater weight loss than non-surgical treatments.³⁸ Significant improvements of obesity related co-morbidities such as diabetes, hypertension, and dyslipidemia have also been documented.^{38,39} However, individuals who have undergone these surgeries require ongoing postoperative management, including assessment of preexisting co-morbidities, evaluation of potential complications, and proper monitoring of nutritional status in order to prevent any nutritional deficiencies.⁴⁰

The use of FDA-approved pharmacological interventions for the treatment of obesity is another therapeutic option. This type of intervention should only be considered as an adjunct to lifestyle changes, such as diet, exercise, and behavioral modification. It is recommended for individuals with a BMI of 30 or greater, or a BMI of 27 or greater with obesity related co-morbidities such as hypertension or diabetes.^{36,37} These drugs can be classified in the following categories based on their mechanism of action: appetite suppressants, fat

absorption reducers, and boosting of energy expenditure and thermogenesis.^{41,42}

There are currently three FDA-approved weight loss medications that are used for long-term treatments, Lorcaserin, Phentermine/topiramate, and Orlistat.⁴³ In 2012, the Food and Drug Administration (FDA) has approved two of these medications as adjuncts to a reduced-calorie diet and increased physical activity.⁴⁴ Lorcaserin⁴⁵ works as an appetite suppressant by activating central serotonin 2C receptors, which are responsible for regulating energy and glucose homeostasis.^{45,46} Phentermine/topiramate is a combination of two different FDA approved drugs: phentermine, an appetite suppressant, and topiramate, which is used for the treatment of epilepsy.^{46,47} These drugs not only have been successful with reducing weight, but also have been shown to reduce blood glucose levels, blood pressure, and serum lipid levels.⁴⁴

Orlistat, marketed as Xenical in the US and Canada, is a lipase inhibitor that works in the gastrointestinal tract by blocking lipase and consequently reducing fat absorption by approximately 30 percent.^{48,49} Treatment with Orlistat must be combined with a reduced calorie and 30 percent fat diet.^{42,50} Consuming foods high in fat while taking this medication may cause negative gastrointestinal side effects such as fatty stools, fecal urgency, and oily spotting.⁵¹ As a result, fat-soluble vitamins such as A, D, E, and K are often diminished; therefore, adequate vitamin supplementation in conjunction with Orlistat is recommended.⁵¹ Numerous studies have shown the efficacy of Orlistat with an average weight loss of 2.9 kg compared to participants receiving placebo.⁵¹

In general, obesity medications for long-term treatment, when combined with lifestyle interventions, have been shown to produce additional weight losses ranging from approximately 3 percent to 9 percent.⁵² Additional weight loss medications, which are used for short-term treatment, include Diethylpropion, Phentermine, Benzphetamine, and Phendimetrazine.⁵³ The mechanism of action of these medications is similar to those of amphetamines; they stimulate the release of norepinephrine, which increases heart rate and blood pressure, producing a decrease in appetite.⁵⁴ These FDA-approved medications should not be used for more than 12 weeks, as they are controlled substances and may potentially lead to physical dependence. Also, due to possible side effects, these medications are not recommended for individuals who suffer from heart disease, high blood pressure or hyperthyroidism.⁵³ Therefore, before prescribing these medications, a thorough evaluation of the potential benefits versus the possible risks must be performed by a physician.

Lifestyle interventions and behavioral modification focusing on decreasing caloric intake and increasing caloric expenditure are among the most useful strategies for the management of childhood, adolescent, and adult obesity.⁵⁵⁻⁵⁹ The key element to a successful weight loss intervention depends on creating an energy deficit, which occurs when individuals consume fewer calories than they expend. The magnitude of the differences in weight outcomes depends on the degree of energy deficit created. An energy deficit of 500 to 1000 kcal/day is recommended, which will result in a weight loss of 1 to 2 pounds per

week. Therefore, such a reduction in caloric intake will result in slow, but progressive, weight loss of approximately 10 percent after 6 months.³⁷ In addition to reducing caloric intake, weight management interventions focus on increasing physical activity as an adjunct to weight loss and weight maintenance.

Physical activity is an important component of a successful long-term weight loss program. Physical activity can also have a positive effect on health outcomes of obesity-related comorbidities and risk factors such as high blood lipid levels and high blood pressure. The evidence suggests that moderate intensity of physical activity for 30 to 45 minutes, 3 to 5 days per week is initially recommended. However, for most obese individuals, exercise should be initiated slowly, and the intensity should be increased gradually, starting with small tasks such as taking the stairs or walking, and slowly building up to more strenuous activities such as fitness walking, cycling, or rowing.³⁷ Although numerous studies have shown that exercise alone has a minimal effect on weight loss,⁶⁰⁻⁶³ it appears that exercise has a crucial role in maximizing long term weight loss and preventing weight regain.^{59,64} To optimize weight maintenance, a prospective study found that an average of 80 min per day of moderate activity, or 35 min per day of vigorous activity is necessary to prevent weight regain in previously obese women.⁶⁵ Furthermore, it has been shown that physical activity in combination with a reduction in energy intake may result in a greater weight loss when compared with dietary modification alone.^{37,66}

The effectiveness of physical activity combined with dietary restrictions

has been shown to produce a 20 percent greater initial weight loss than dietary restrictions alone.⁶⁷ Physical activity and diet therapy combined was also more effective at sustaining weight loss than diet alone after one year.⁶⁷ In addition, findings suggest that overweight and obese individuals using dietary restrictions in combination with physical activity experience significant improvements in total cholesterol, LDL-C, and total cholesterol/HDL-C ratio.⁶⁸ Therefore, the implementation of a successful lifestyle intervention focusing on decreasing energy intake and increasing energy expenditure can result in significant weight loss and improvements in health outcomes in overweight and obese individuals.⁶⁹

In addition to implementing changes to dietary and physical activity patterns, behavior modifications are integral components of successful obesity interventions. Behavioral based lifestyle interventions focus on self-monitoring of dietary and physical activity, goal setting, stimulus control, problem solving, cognitive restructuring, and relapse prevention.⁷⁰ A key component of a successful behavioral weight loss program is self-monitoring of dietary intake, which includes daily recording of all foods and beverages consumed.⁷¹⁻⁷³ Studies have shown that self-monitoring strategies focusing on tracking dietary intake are significantly associated with greater weight loss and successful weight management.⁷⁴⁻⁷⁶ These interventions serve to increase an individual's self-awareness and accountability, and encourages a self-reinforcing attitude towards any successful lifestyle intervention.⁷⁵

Self-monitoring is often described as the cornerstone of behavioral intervention for obesity.^{71,77,78} Individuals have traditionally used the diary-based, paper and pencil method as a self-monitoring strategy.⁷⁵ However, this method is perceived to be time-intensive, tedious, and subject to inaccuracies of self-report.^{72,79,80} Personal diaries also lack the benefits of immediate real-time external feedback, such as tailored email or text reminders to support and motivate individuals on health-related decisions, which further diminishes the effectiveness and appeal of this method.⁸⁰ However, in recent years advances in technology have provided a variety of self-monitoring options that involve greater automation, tailoring, flexibility, and interaction.⁷⁹ With the arrival of computer and Internet based technologies, a variety of tools for self-monitoring of health behaviors, such as Internet websites and smartphone device applications, are now available.

A number of smartphone applications (apps) that use the computational abilities of the phone for self-monitoring have been developed that allow individuals to record dietary data with relative ease and provide real-time feedback on progress, such as toward a daily goal of caloric intake.⁸¹⁻⁸³ Examples of these apps include Lose It, Tap & Track, Nutrition Menu, and MyFitnessPal. All of these products require manual input of all foods and portion sizes, to calculate energy and nutrient consumption. The Lose It, Tap & Track and MyFitnessPal apps offer both a smart-phone application and a web site version. Individuals can use either one or both versions, as they can be linked to one

another, allowing both platforms to be highly portable and convenient to use. In addition, the Lose It and MyFitnessPal apps offer many benefits to users, such as social networks, online forums, and data sharing capabilities. However, despite the benefits they offer, these sophisticated tools rely on the individual's memory and accurate recall, and the ability to estimate portion size, which may potentially lead to underreporting of dietary intake.

Overview of Image-Assisted Dietary Assessments

Technologies for self-monitoring of health behaviors have been shown to be effective, however these methods still require individuals to rely on memory and accurate recall. Therefore methods of collecting dietary intake data that do not rely on memory would be preferable for assessing the effects of diet on nutritional status and health. The use of images can potentially address the weaknesses described above, and provide a superior platform for recording dietary intake for self-monitoring and dietary assessment.

One of the earliest image-capable devices that were used to address the potential weakness of memory recall of dietary intake were the personal digital assistants (PDAs). Wang et al.⁸⁴ studied these devices as tools for capturing food images, suggesting that they may be a valid and convenient method for evaluating dietary intake. They examined the validity and reliability of an image-based food records approach, using a hand-held personal digital assistant with camera capability. Images of foods and drink were captured before and after

eating, at a 45-degree position with a ruler-like stylus placed beside foods as a reference in all images. The captured images were transferred to a mobile phone card attachment within the PDA and were sent to the dietician for estimation of the daily nutrient intakes. By capturing images of an individual's daily dietary intake, there was no significant difference when compared with the written food record for most nutrients. Also, using this image-based food record approach was found to be less burdensome than weighed food records, and the time it took to record the daily diet was shorter, at 16 minutes compared to 37 minutes using weighed food records.⁸⁴ However, in a larger validation study, nutrient intakes estimated by this image-based food record approach had significantly lower values for all macronutrients compared with the weighed diet record method, and underestimated mean energy intake (EI) by 13.1 percent.⁸⁵ In addition, the low quality of the digital image made it difficult to accurately calculate nutrient intakes, resulting in excluding consumed foods and underestimating energy intake.⁸⁵ Also, the images taken had to be transferred to a mobile phone card and physically sent to a registered dietician for analysis. As a result of these technological barriers, improving the image quality and utilizing web-based technology may improve food identification and facilitate the collection of images for dietary analysis.

Mobile phone applications that integrate digital cameras with web-based technology have become desirable tools for nutrition researchers to record dietary intake, leading to the development of novel methods of dietary

assessment.⁸⁶⁻⁹⁵

Martin et al⁹² conducted a study on the feasibility of the Remote Food Photography Method (RFPM) in free-living conditions. The RFPM consists of camera-enabled mobile phones with capabilities to transmit images to a server via a cellular network. This pilot study focused on energy intake in free-living conditions compared to the gold standard method of doubly labeled water (DLW). The DLW technique is a validated method for the measurement of energy expenditure in free-living subjects. It involves the administration of stable isotopes (hydrogen and oxygen) to form water. The estimate of energy expenditure is calculated by measuring the difference between the isotope elimination rates, and the production of carbon dioxide.⁹⁶ The results of this pilot study showed no significant difference in energy intake measurements between the RFPM when compared with DLW technique. The RFPM underestimated energy intake by only 3.7 percent in free-living conditions. In addition, there was no link with under eating when capturing images with the RFPM.

To further improve the underestimation of energy intake with RFPM, Martin et al⁹² utilized prompts to increase the accuracy in recording energy intake in free-living conditions. The objective of this follow-up study was to test two prompt approaches: a standard prompt and a customized prompt, which varied in the number of prompts the participants received per day and time of delivery.⁹² Forty overweight and obese participants were instructed to record their dietary intake over six days in free-living conditions to assess total energy

intake using the RFBM and the DLW method. Participants (n=24) in the standard group received 2 to 3 prompts per day via emails or text messages around standard meal times, whereas the customized group (n=16) received 3 to 4 prompts per day around participants' usual mealtime. The overall results showed that when standard prompts were used, energy intake estimated with the RFBM significantly differed from energy intake estimated with DLW. However, in the customized group, energy intake estimated with the RFBM did not significantly differ from energy intake measured with DLW. The difference in energy intake between RFBM and DLW in the customized prompt group was significantly smaller compared to the standard prompt group. With the use of customized prompts within image-based applications, there is a promising future in accurately assessing energy intake in free-living conditions.

These studies have utilized various image-based capabilities to record food intake in an attempt to improve dietary reporting. However, these methods continue to depend on users remembering to capture images to record food intake. Therefore, researchers have focused on improving the dietary recall by capturing images automatically. The advancement of new technology has allowed investigators to introduce wearable camera technology.^{95,97-99} In a study by Arab et al⁹⁵ the capability of the wearable camera to capture automatic images every 10 seconds was used to test the feasibility of this approach. Mobile phones equipped with three-mega pixel cameras were used to capture automatic images. The automatic images were transferred to a web application and

accessed by the participants to assist with the analysis of the 24- hour recalls, which 93 percent of participants found the images to be “helpful” or “sort of helpful”. Although most of the participants were new to this type of technology, 79 percent reported not having any technological issues with using this device.⁹⁵ However, wearing these cameras was rated as too intrusive and burdensome by 71 percent of participants,⁹⁵ discouraging them from using this means of technology, especially in a public setting. Furthermore, due to the every 10 second image capture, it was found to be extremely time consuming and labor intensive for participants to sort through the enormous number of images that are generated throughout the course of a day. Finally, the cameras have limited battery life and a narrow field of view, further limiting their usefulness.

Gemmin et al⁹⁸ recognized these limitations and developed an enhanced wearable camera that captures automatic wide-angle point-of-view images every 20-30 seconds. These investigators conducted a feasibility study to examine if images taken by the wearable camera can improve the analysis of an interviewer-administered 24-hour recall in a sample of 20 healthy adults. Participants were instructed to wear the camera for 2 days while performing their everyday activities. On day 3, the images taken by the wearable camera were used to assist participants with an interviewer-administered 24-hour recall. The 24-hour recall was performed by a trained dietician, and was based on the previous 24-hour dietary intake. Energy and nutrient intakes were measured by comparing the 24-hour recall (without images) to the 24-hour recall in combination with images.

The results indicated that the use of images increased mean EI by 12.5 percent (2,738 +/- 502 kcal vs 3,080 +/- 712 kcal; P=0.02) compared with using the 24-hour recall alone.⁹⁸ The reason for the increase was mainly due to reporting 41 additional foods by viewing the camera images. Although these investigations showed promising results, there are some important limitations. Participant feedback indicated that although the use of images helped with recall, wearing these cameras may have affected individual eating behaviors, resulting in misrepresentation of usual intake. Also, wearing these cameras felt uncomfortable, especially in a public setting. There are also limitations concerning the camera technology. The quality of the images in low-light environments were poor, posture and body shape affected lens angle, resulting in non-useful images, and the frequency of images taken was too slow to capture of all foods consumed.⁹⁸

Advances in smartphone technology may provide an enhanced mechanism for collecting dietary intake. The powerful technical capabilities of smartphones offer unprecedented opportunities for collecting dietary information, which can enhance dietary assessments and address many of these limitations. The use of mobile phone technology continues to grow rapidly, with 90 percent of American adults owning a mobile phone as of 2014.¹⁰⁰ About 64 percent of all mobile subscribers were smartphone users, and 40 percent were Apple iPhones users.^{100,101} Smartphones have now become more than just a means of communication; they have additional functionalities such as Internet

access, high-resolution camera with autofocus, as well as GPS and WiFi capabilities. These devices can also be used as a mobile terminal for e-commerce and value-added services such as timely access to information, immediate purchase opportunity, and bank transactions. Finally, one of the most useful features of smart phones is their capability to run applications (apps) created by third party developers. Therefore, the utility of smartphones for health and wellness purposes has attracted the attention of researchers, industry, and the public. According to the finding from the Fifth Annual Makovsky/Kelton "Pulse of Online Health" Survey,¹⁰² about 66 percent of US adults are interested in using a smartphone application to help manage their health and wellness. Among interested respondents, 47 percent wanted to use smartphone apps to track dietary intake and nutrition, which was the top interest expressed by participants.

Software developers have created valuable applications (apps) for smartphones to assist in the collection and assessment of dietary intake. Researchers from the University of Arizona have developed an image-based dietary assessment app called the Recaller, which uses a smartphone with camera and Internet capabilities to help individuals record and recall their dietary intakes.⁸⁹ Using the Recaller app, smartphone images of foods were captured before and after an eating event, and then securely uploaded to a server on the Recaller website in real-time, and later accessed for analysis by a trained nutritionist. This pilot study focused particularly on the usability of the Recaller

app, with written questionnaires assessing the overall ease of use by participants. Most respondents reported that the app was extremely easy or easy to use, and 50% of all participants would consider using this app on a daily basis. However, the other half of all participants considered the use of the app as cumbersome, and would not be willing to use the app in the future. These participants reported not remembering, or not wanting to bother to take pictures of all foods consumed. Also, a substantial number of participants wanted to see more nutritional information or receive feedback on their dietary intake. This study focused only on the usability of the Recaller app, however allowing the participants to review the images and providing them with nutritional information may enhance their willingness to capture images.

Another goal of image based dietary intake monitoring is to develop tools that can not only reduce a user's burden, but also provide accurate estimations of dietary intake using image-processing algorithms. Researchers from Purdue University and the University of Hawaii Cancer Center have been working on developing an image analysis system that would be capable of automatically estimating energy and nutrient intake from images taken by smartphones.¹⁰³ This system, known as Technology Assisted Dietary Assessment (TADA), uses a newly developed mobile phone food record (mpFR) application, which can be used on both iOS and Android devices. The mpFR application uses a smartphone device with a built in camera to take images of food to record dietary intake. These images are taken before and after eating and automatically

uploaded for analysis. When taking images of foods, individuals are instructed to use a fiducial marker, which serves as a reference of known dimensions and markings.

The TADA system and the associated mpFR are designed to automatically identify foods using image analysis techniques. Automatic image analysis for identification and quantification of food consumption is based on the following stages: image-processing,^{104,105} image segmentation,^{103,106-108} feature extraction and classification,^{103,108} volume estimation,^{103,108} and calorie and nutrient estimation.¹⁰³ These strategies are sophisticated methods, which focus on correcting the image quality, isolating food items, extracting color and texture features, estimating volume with 3D images, and converting the density of the food by using X-ray computerized microtomography (XMCT) and 3D laser imaging. However, these researchers have noted that some foods may not be identifiable based only on a single image. For example, it would be difficult to distinguish the type of milk consumed in a cup (e.g., low fat or skim milk). Therefore, more detailed information on how the food was packaged or manual/audio inputs from the participants will be required.¹⁰⁸ Currently, the researchers that have developed the TADA system are only in the beginning stages. Their ultimate goal is to expand this system to include a nutrient database and improve the image processing system to identify, quantify, and accurately estimate foods consumed by users.

Recently, we have developed an enhanced smartphone application called

MyEnergyBalance, which permits imaged-based self-monitoring of all foods consumed, and offers a convenient, inexpensive and user-friendly web-based dietary assessment tool. The MyEnergyBalance tool consists of both an iPhone app and a website. It was designed primarily as a learning tool for college students to assist with recording daily food intake, thus allowing students to accurately measure their energy intake. In addition, it is designed to examine various nutrients; generate reports of individuals' energy intake and energy expenditure analysis; and generate a prediction of energy balance and the effects it may have on weight loss, weight gain, weight maintenance or overall health. The MyEnergyBalance tool is also intended for individuals to use as a self-monitoring tool in conjunction with weight loss programs.

The MyEnergyBalance iPhone app integrates several capabilities designed to enhance food recall including image, audio and text inputs. These features will potentially improve the problems of underreporting by providing individuals with visual, audio, and text reminders while recording their daily dietary intake. Although researchers have studied the usability of a similar app (Recaller app), there have been no studies that examined the effectiveness and validity of the image, audio, and text reminders at improving dietary recall and analysis by users.

The goal of our research study is to determine if the MyEnergyBalance iPhone app and website improves food recall compared to other non-image-based food recall methods. In order to accomplish this, it is necessary to select a

validated reference method for comparison. The primary dietary assessment instruments used as reference methods in epidemiological studies include food records, food frequency questionnaires, interviewer-based 24-hour recalls, and Automated Self-administered 24-hour dietary recalls (ASA24). As a comparison method, the ASA24 offers important advantages over the other methods. ASA24 is a freely available web based assessment. It was developed by the National Cancer Institute (NCI) and it consist of two web based applications. The Respondent web site is used for participants to complete their dietary recall, and a Researcher web site is used by researchers to monitor studies and obtain data analyses. The major advantages of this assessment tool over other methods are its convenience (compared to interviewer administered recall method) and its relative cost effectiveness. Recently, validation studies have found a strong correlation between the ASA24 dietary assessment method and a 4-day diet food record in a sample of university-affiliated adults.¹⁰⁹ Also, the ASA24 was highly correlated when compared to plate waste, true intake, and the standard interviewer-administered, Automated Multiple-Pass Method (AMPM) 24-hour dietary recall.^{110,111}

Smartphone applications that utilize images, audio, and text have a promising future in dietary assessments. We hypothesize that the use of MyEnergyBalance smartphone app to take images of foods throughout the day in combination with the MyEnergyBalance website will result in dietary analysis closer to the Automated Self-Administered 24-hour dietary recalls (ASA24)

versus using the MyEnergyBalance website alone without iPhone images.

CHAPTER 2

ABSTRACT

The powerful technical capabilities of smartphones offer unprecedented opportunities for collecting dietary information. We have developed an enhanced smartphone application called MyEnergyBalance, which permits imaged-based self-monitoring of all foods consumed, and links to a convenient and user-friendly web-based dietary assessment tool. The primary objective of this pilot study was to determine if the MyEnergyBalance app (with use of images) in combination of the associated website improves dietary recall compared to diet analysis on the MyEnergyBalance website alone. We also generated preliminary data on the usability of the MyEnergyBalance iPhone app and website. This pilot study was a crossover study design of healthy, college students. Participants were randomly assigned to two groups. Both groups consumed their normal diet for the first day with one group recording their food intake with image functions of the MyEnergyBalance app, while the other group did not use the app. On the second day, all participants logged into the MyEnergyBalance website to record their food intake from the previous day; one group using the images from the app to assist in recalling what they ate, while the other group recalled what they ate from memory. The diet analysis results were compared to those obtained using the ASA24 website. The groups were then crossed over to the opposite vs no-image assisted recalls. Ten participants (seven females and three males) aged 20 to 22 years completed this study. The average BMI of all participants was 23.12 kg/m² (ranging from 18.95 to 32.28 kg/m²). There was no statistically significant differences in the estimates of the energy intake between the MyEnergyBalance app and website compared to ASA24. The SUS mean score for the MyEnergyBalance app and website was 86 and 69.5, respectively. A strong, negative correlation was found between the system usability scale scores and the absolute differences in energy intake of the MyEnergyBalance app and ASA24. Although we were not able to demonstrate a significant benefit of the images from the iPhone app at improving food recall (perhaps due to the small study sample size), we were able to demonstrate a high usability score for the iPhone app, average usability score for the website, and a significant correlation between subjects' usability scores and relative accuracy of the subjects' food recall using the images from the iPhone app. A future study with a larger sample size will hopefully provide more information on the efficacy of image-based food recalls.

INTRODUCTION

Obesity has reached epidemic proportions in the United States and has become one of our nation's most pressing public health concerns. The prevalence of overweight and obesity has increased significantly among US adults in recent years, with more than two-thirds of the adult population in the US considered overweight or obese as of 2012.¹ Obesity has also been associated with a higher prevalence of disability²⁻⁴ and increased mortality⁵⁻¹² among US adults. Obesity is a complex condition resulting from an imbalance between energy intake and energy expenditure.¹³ A number of weight management interventions for overweight and obese individuals are available, including surgical procedures, pharmacologic, dietary, modifying physical activity patterns, behavior therapy, as well as combinations of these interventions.^{14,15} Lifestyle interventions and behavioral modification focusing on decreasing caloric intake and increasing caloric expenditure are among the most effective strategies for the management of obesity.¹⁶⁻²⁰

Self-monitoring is often described as the cornerstone of behavioral intervention for obesity.²¹⁻²³ Studies have shown that self-monitoring strategies focusing on tracking dietary intake are significantly associated with greater weight loss and successful weight management.²⁴⁻²⁶ These interventions serve to increase an individual's self-awareness and accountability, and encourage a self-reinforcing

attitude towards any successful lifestyle intervention.²⁵ Individuals have traditionally used the diary-based, paper and pencil method as a self-monitoring tool.²⁵ However, this method is perceived to be time-intensive, tedious, and subject to inaccuracies of self-report.²⁷⁻²⁹ With advances in computer and Internet based technologies, a variety of tools for self-monitoring of health behaviors, such as Internet websites and smartphone device applications, are now available.

The powerful technical capabilities of smartphones offer unprecedented opportunities for collecting dietary information, which can enhance dietary assessments and address many of the limitations associated with paper and pencil food diaries. A number of smartphone applications (apps) that use the computational abilities of the phone for self-monitoring have been developed that allow individuals to record dietary data with relative ease and provide real-time feedback on progress, such as toward a daily goal of caloric intake.³⁰⁻³² However, despite the benefits they offer, these sophisticated tools continue to rely on the individual's memory and accurate recall, as well as the ability to accurately estimate portion size, which may potentially lead to underreporting of dietary intake. The use of images can potentially address these weaknesses and provide a superior platform for recording dietary intake for self-monitoring and dietary assessment. Mobile phone applications that integrate digital cameras with web-based technology are becoming important tools for nutrition researchers to record dietary intake, leading to the development of novel methods of dietary assessment.³³⁻⁴²

We have recently developed an enhanced smartphone application called MyEnergyBalance, which permits imaged-based self-monitoring of all foods consumed, and links to a convenient and user-friendly web-based dietary assessment tool. The complete MyEnergyBalance tool consists of both an iPhone app and a website. It was designed primarily as a learning tool for college students to assist with recording daily food intake, thus allowing students to accurately measure their energy intake. In addition, it is designed to examine various nutrients, generate reports of individuals' energy intake and energy expenditure analysis, and generate a prediction of energy balance and the effects it may have on weight loss, weight gain, weight maintenance or overall health. The MyEnergyBalance tool is also designed for use by individuals as a self-monitoring tool in conjunction with weight loss programs.

The MyEnergyBalance iPhone app integrates several capabilities designed to enhance food recall including image, audio and text inputs. These features will potentially improve the problems of underreporting by providing individuals with visual, audio, and text reminders while recording their daily dietary intake, and subsequently analyzing their diets on the MyEnergyBalance website.

Although other researchers have studied the usability of a similar app (Recaller app)³⁶, there have been no studies published to date that examined the effectiveness and validity of the image, audio, and text reminders at improving dietary recall and analysis by users.

The goal of our pilot study was to generate preliminary data on the validity of the MyEnergyBalance iPhone app and website. The preliminary data will be used for a power and sample size calculation for a future larger validity study. An additional objective of this research study is to obtain preliminary usability data on the MyEnergyBalance app and website. The usability data will be important as we work to make improvements in future version of the MyEnergyBalance app and website. We hypothesize that the use of MyEnergyBalance smartphone app to take images of foods throughout the day in combination with the MyEnergyBalance website will result in dietary analysis closer to the results obtained using the Automated Self-Administered 24-hour dietary recalls (ASA24) versus using the MyEnergyBalance website alone without iPhone images.

MATERIALS AND METHODS

The MyEnergyBalance app and website

The MyEnergyBalance iPhone app integrates several capabilities designed to enhance food recall including the ability for users to take pictures of food, as well as enter audio and text descriptions of what they have eaten. The homepage menu on the MyEnergyBalance iPhone app (see Figure 1.) consists of functions and features related to energy intake (allowing individuals to take images of foods), and energy expenditure (allowing individuals to account for all activities over a 24 hour period). The “Report” function allows individuals to generate and

view reports of their diet, activities, and energy balance. Users can use the iPhone app to capture images of all foods and beverages consumed. In addition, individuals could also record an audio and text comment about their food consumed. These images are automatically transferred to the MyEnergyBalance website and later accessed by the users to assist with the analysis of the 24-hour recalls. This app is now available for free download from the Apple “App Store”.

The MyEnergyBalance website is designed to examine various nutrients; generate reports of individuals’ energy intake and energy expenditure analysis; and generate a prediction of energy balance and the effects it may have on weight loss, weight gain, weight maintenance or overall health. The images of foods taken with the corresponding app are automatically uploaded to the MyEnergyBalance website and accessed for analysis by users. Using the iPhone-captured images as recall reminder, users match their foods with the USDA food and nutrient database for nutrient analysis.⁴³ The website also includes short tutorials (with links to more detailed tutorials) on use of the iPhone app, a tutorial on use of the website, and a tutorial designed to assist users in estimating portion sizes when analyzing their diets. These tutorials are freely available for viewing and can be accessed by the following links.

iPhone Tutorial: https://www.youtube.com/watch?v=Y61OnciaT_M

Website Tutorial: <https://www.youtube.com/watch?v=8CODqSFA9qY>

The website can be accessed by going to www.myenergybalance.net.

STUDY SAMPLE

The University of Vermont, Committee on Human Research in the Behavior Sciences (Institutional Review Board), approved this study protocol. Study participants who were greater than 18 years of age were recruited from the University of Vermont student population, through announcements in classes. Interested study participants were directed to contact the study investigator and were presented with a detailed description of the study and a brief questionnaire to confirm that they have the necessary smartphone equipment. After the participants signed a written informed consent form, they were directed to view video tutorials on installation of the iPhone app, personal account creation, and use of the MyEnergyBalance app and website. Demographic information including age, gender, height, weight, and BMI were also collected. All participants received a compensation of \$100 in the form of an Amazon gift card for completion all study requirements.

STUDY DESIGN

This study was a crossover design, and a flow diagram of the study design is presented in Figure 2. Prior to beginning the study, all participants were instructed to install the MyEnergyBalance app on their smartphones. For the first two days (Training Days One and Two in Figure 2), study participants practiced using the MyEnergyBalance smartphone app and website diet analysis tool, as well as practice reporting and analyzing their diets with the ASA24 tool. The

participants then were randomized into two groups. Both groups consumed their normal diet for the first test day (Day One in Figure 2), with one group recording their food intake with the image (as well as audio and text) functions of the MyEnergyBalance app, while the other group did not use the app. All participants then met with the study investigator on Day Two. At this meeting, users logged into their MyEnergyBalance website accounts. The group that had recorded their food intakes the previous day using the app camera saw all of their captured food images, audio, and text details in their diet analysis account page. The group that did not use the app would need to try and recall from memory everything that they ate the previous day and enter it manually into their MyEnergyBalance account. Once both groups completed their MyEnergyBalance diet analysis on the website, they immediately logged into the ASA24 diet analysis program. The ASA24⁴⁴⁻⁴⁶ is a validated web based dietary recall and analysis program developed by the National Cancer Institute (NCI). The ASA24 method systematically assists users in recalling everything that they ate on the previous day. In effect, the ASA24 will perform a “recheck” of their MyEnergyBalance analysis of their previous day’s diet. As this is a crossover study design, one group used the smartphone images to assist with diet recall on the first day of diet analysis, and then crossed over to consume the next study day’s diet without the use of smartphone images.

Following completion of all diet analysis, users evaluated the usability of the MyEnergyBalance tool by completing the System Usability Scale (SUS) for both

the app and website. The “System Usability Scale” (SUS)^{47,48} is a free, simple, 10 question validated tool for generating a usability “score”. These surveys provide a single score on a scale from 0 to 100, where higher scores indicate better usability. The average SUS score for Internet-based Web pages and applications obtained from approximately 500 studies in which it was used was 68.^{47,48}

DATA COLLECTION AND STATISTICAL ANALYSIS

Agreement between diet analysis obtained from the MyEnergyBalance website and the ASA24 was examined. The following nutrient items were included in the analysis: energy (kcal), carbohydrate (g), protein (g), total fat (g), sodium (mg), iron (mg), calcium (mg), vitamin C (mg), and beta carotene (ug).

Differences between values for these nutrients/energy obtained from the diet analysis on the MyEnergyBalance website versus the ASA24 methods were statistically analyzed by paired t-tests. We also collected data on gender to determine if there were any differences between females and males for the comparisons.

A correlation coefficient was calculated to determine if there was any statistically significant relationship between the participants’ System Usability Scale scores and the accuracy of their diet analysis results using the MyEnergyBalance app (relative to the ASA24 analysis). A correlation coefficient was also calculated to determine if there was a statistically significant relationship between the participants’ System Usability Scale scores and the accuracy of their diet analysis

using only the MyEnergyBalance website, without image reminders (relative to the ASA24 analysis).

RESULTS

There were ten participants (seven females and three males) aged 20 to 22 years that completed this study. The mean age of all participants was 20.5 years (ranging from 20-22 years). Average height was 67 inches and average weight was 149 pounds. The average BMI of all participants was 23.12 kg/m² (ranging from 18.95 to 32.28 kg/m²).

As can be seen in Table 1 we compared the mean energy and macronutrients intake measured with the MyEnergyBalance app and website to the same day's diet analyzed using the ASA24 method. When completing the dietary analysis using the MyEnergyBalance website, individuals who used the MyEnergyBalance app to take images of all foods consumed did not have any statistically significant differences in the estimates of the energy intake compared to the ASA24 results. However, there was a significantly less estimated amount of protein when compared to the estimated amount using the ASA24 recall (50.7g vs 65.8g, respectively; p=0.02). When completing the dietary analysis using the MyEnergyBalance website (without the use of the iPhone app food image reminders), there was no statistically significant differences in the estimates of the energy intake. However, there was a significantly less estimated amount of cholesterol when compared to the estimated amount using the ASA24

recall (128.3mg vs 193.0mg; $p=0.02$). In order to determine if there was any gender effects, we separately analyzed the female ($n=7$) and male ($n=3$) participants. There was no significant effect of gender on either diet analysis obtained using the iPhone app (with images) or the website alone (without images) compared to the ASA24 results.

Tables 2 and 3 provides data describing the individual System Usability Scale (SUS) scores and the overall raw SUS for the MyEnergyBalance app and website, respectively. The SUS score for the MyEnergyBalance app was 86 (SD, 8), and the SUS score for the MyEnergyBalance website was 69.5 (SD, 18.7). The overall user-friendliness was based on a 7-point scale. In addition, study participants were asked one summary question (“Overall I would rate the user-friendliness of this [app or website] as..”) based on a seven point scale from “worst imaginable” to “best imaginable.” For this question, the MyEnergyBalance iPhone app scored 5.8 (SD 8) and the MyEnergyBalance website scored 4.6 (SD 0.8).

A correlation analysis was conducted to evaluate if there was a relationship between the System Usability Scale scores and the absolute difference of energy intake between the MyEnergyBalance app (images were used) and the ASA24 recall. Initial analysis found no significant relationship between the System Usability Scale scores and the MyEnergyBalance app (Figure 3). However, when one outlier subject was removed from the analysis, a statistically significant negative correlation was found between the System Usability Scale scores and the absolute difference of energy intake between the MyEnergyBalance app and

the ASA24 recall (Figure 4). Therefore, the higher the System Usability Scale score, the smaller the difference between the absolute difference in energy intake between the MyEnergyBalance app and the ASA24 recall.

A correlation analysis was also conducted to evaluate if there was a relationship between the System Usability Scale scores and the absolute difference of energy intake between the MyEnergyBalance website (no images were used) and the ASA24 recall. There was no statistical significance found between the System Usability Scale scores and the MyEnergyBalance website (Figure 5). However, after removing the same outlier participant from the analysis, a weak negative correlation was noted ($r=-0.47$, $p=0.20$) (Figure 6).

DISCUSSION

This was a pilot study to generate preliminary data on the accuracy of the MyEnergyBalance iPhone app and website. The majority of the participants in our study were healthy college students and their BMI indicated that the majority of them had normal weight with an exception of one individual who was obese. Our initial hypothesis was to see if the use of the MyEnergyBalance app (with the use of images) in combination with the MyEnergyBalance website would result in dietary analysis closer to the results obtained using the Automated Self-Administered 24-hour dietary recalls (ASA24) versus using the MyEnergyBalance website alone (without the use of images). However, we did not see any significant results in the estimates of the energy intake between the

MyEnergyBalance app (with the use of images) in combination with the website compared to ASA24 versus the MyEnergyBalance website (without the use of images) compared to ASA24. Although there was a statistically significant difference with the protein intake in the MyEnergyBalance app and website and the cholesterol intake in the MyEnergyBalance website alone, we believe these results were due to chance and could be better confirmed with a larger sample size.

All participants evaluated the MyEnergyBalance app and website using the System Usability Scale tool. The average SUS score for web pages and applications obtained from approximately 500 studies in which it was used was 68.^{47,48} The SUS score for our MyEnergyBalance app was 86, which was higher than the average score of 68. In general, an SUS score of 80 is considered to be in the top tenth percentile, which is closely associated with the likelihood that users would recommend this app to friends.⁴⁸ Although the overall SUS score for the MyEnergyBalance app was 86, there was a neutral rating to the statement asking if participants would use this app frequently. The SUS score for the MyEnergyBalance website was 69.5, which is approximately equivalent to the average score of 68 placing the website at the 50th percentile. In addition to this score, there was a low rating to the statement asking if participants would use this app frequently.

As discussed earlier, we did not see any significant differences with the overall energy intake between the MyEnergyBalance app and website compared to the ASA24. However, we were interested to see if there was any correlation between the system usability scale scores and the absolute differences in energy intake with the MyEnergyBalance app and ASA 24 as well as the MyEnergyBalance website and ASA24. After removing one subject outlier from the analysis, a significant negative correlation between the SUS scores and the absolute differences in energy intake between the app and the ASA24 results was noted. Participants who rated the MyEnergyBalance app higher on the system usability scale had a smaller absolute difference between the MyEnergyBalance app and ASA 24 energy intake. A similar but not statistically significant negative correlation was noted between the system usability scale scores and the absolute differences in energy intake between MyEnergyBalance website and ASA24. In a future study we will include focus group analysis to help identify the specific aspects of the app and website that contribute to their usability.

An additional objective of this pilot study was to generate preliminary data from which a sample size power calculation would be determined for a future larger study. Based on the results of this pilot study, we determined that we would need 140 participants to be able to detect a difference of 5% between the energy intake obtained with the MyEnergyBalance iPhone app versus the ASA24 with a power of 0.80 and a two-sided alpha of 0.05. We also determined that we would need 37 participants to be able to detect a difference of 10% between the energy

intake obtained with the MyEnergyBalance iPhone app versus the ASA24 with a power of 0.80 and a two-sided alpha of 0.05.

Due to our small, relatively homogenous sample of young, healthy, college students, our results cannot be applied to the general population. Testing the accuracy and generalizability of a food recall tool will be influenced by the age, sex, and BMI of the study participants.⁴⁹ Specifically, underreporting of energy intake is more prevalent in obese individuals.^{50,51} However, due to our small sample size, we did not see this result. Therefore, a future, robust study must be conducted with a larger, diverse study population representing a wide range of BMI's to evaluate whether the MyEnergyBalance tool can demonstrate a significant benefit on the efficacy of image-based food recalls.

CONCLUSIONS

This was a pilot study to generate preliminary data on the accuracy and usability of the MyEnergyBalance iPhone app and website. Although we were not able to show that the MyEnergyBalance app (with the use of images) helps with recall of foods consumed, it may be possible to demonstrate this by conducting a study with a larger and more diverse sample size. However, we have demonstrated that our MyEnergyBalance app was rated high for usability.

We are in the process of developing an improved and more user-friendly "version 2" of the MyEnergyBalance smartphone app (for both iPhone and Android platforms) and diet and energy expenditure analysis website. Version 2

of the smartphone app will include an option to receive text message reminders. In addition, version 2 will have the ability to scan food barcodes and have the food information (name of food, servings, calories, nutrient analysis) automatically saved to the user's daily food record and saved in the user's "pantry" for easy recall if they eat the same food at another time. Version 2 of the app will also include integration with the iPhone's build-in "Health" feature that automatically records steps. Users will be able to import their iOS Health app step data directly into the MyEnergyBalance physical activity record, as well as convert these step data to calories expended (which can then be used in the estimation of total daily energy expenditure and energy balance). This pilot study and a future study will both contribute to a better understanding of the role that mobile technologies can play in helping individuals track and improve their diet and exercise health behaviors.

Table 1: Mean energy and macronutrient intake assessed by MyEnergyBalance tool¹ compared with ASA24⁴ recall in college students (n=10)

	MyEnergyBalance App & Website (Image) ² Mean ± SD	ASA 24 Mean ± SD	Mean Difference (%) (%)	MyEnergyBalance Website (No Image) ³ Mean ± SD	ASA 24 Mean ± SD	Mean Difference (%) (%)
Energy (kcal)	1556.8 ± 683.3	1669.1 ± 515.8	112.3 (6.7%)	1713.5 ± 500.8	1842.1 ± 457.3	128.6 (7.0%)
Carbohydrates (g)	209.3 ± 103.4	209.4 ± 91.4	0.1 (<0.1%)	228.0 ± 78.4	235.1 ± 61.8	7.1 (3.0%)
Protein (g)	50.7 ± 20.8	65.8 ± 19.1	15.1 (22.9%) ⁵	56.7 ± 22.2	68.3 ± 20.1	11.6 (17.0%)
Total Fat (g)	60.1 ± 34.5	64.9 ± 23.7	4.8 (7.4%)	68.7 ± 30.7	73.7 ± 27.8	5.0 (6.8%)
Sodium (mg)	2397.7 ± 1108.4	2830.6 ± 1052.5	432.9 (15.3%)	2353.3 ± 1076.0	2943.3 ± 1112.9	590.0 (20.0%)
Iron (mg)	11.8 ± 6.6	14.4 ± 9.7	2.6 (18.1%)	12.0 ± 5.4	12.9 ± 4.7	0.9 (7.0%)
Calcium (mg)	820.1 ± 630.7	929.6 ± 626.2	109.5 (11.8%)	840.8 ± 465.0	800.2 ± 428.2	-40.6 (5.1%)
Vitamin C (mg)	65.2 ± 47.4	78.0 ± 54.6	12.8 (16.4%)	67.5 ± 97.9	67.4 ± 90.4	-0.1 (0.1%)
Cholesterol (mg)	157.9 ± 186.4	205.7 ± 213.9	47.8(23.2%)	128.3 ± 124.0	193.0 ± 156.6	64.7 (33.5%) ⁵

¹MyEnergyBalance tool consists of both an app and website.

²MyEnergyBalance app allows users to take images to enhance food recall; MyEnergyBalance website was used to analyze their diet.

³MyEnergyBalance app was not used, therefore no images were available to enhance food recall; MyEnergyBalance website was used to analyze their diet.

⁴Automated Self-Administered 24-hour (ASA24) system is a validated dietary recall tool.

⁵Mean differences are statistically significant at the p<0.05 level.

Table 2: System Usability Scale Scores for MyEnergyBalance app

Item Number	Question	Mean ± SD
1	I think that I would like to use this app frequently.	3.1 ± 0.9
2	I found the app unnecessarily complex.	4.7 ± 0.5
3	I thought the app was easy to use.	4.6 ± 0.5
4	I think that I would need support of a technical person to be able to use this app.	4.8 ± 0.4
5	I found the various functions of this app were well-integrated.	4.1 ± 0.7
6	I thought there was too much inconsistency in this app.	4.2 ± 1.0
7	I would imagine that most people would learn to use this app very quickly.	4.9 ± 0.3
8	I found the app very cumbersome to use.	4.2 ± 1.3
9	I felt confident using this app.	4.9 ± 0.3
10	I needed to learn a lot of things before I could get going with this app.	4.9 ± 0.3
SUS Score^a		86 ± 8
11	Overall, I would rate the rate the user-friendliness of this app as:	5.8 ± 0.6

Items 1-10: Based on a 5-point Likert Scale (1=Strongly Agree to 5 = Strongly Disagree).

Item 11: Scale based on 7-point Likert scale (1=Worst Imaginable to 7=Best Imaginable)

^aThe SUS Score was calculated by taking the odd numbered items (for Items 1-10) and subtracting one from the user response, and taking the even numbered items and subtracting the user response from five. This scales all values from 0 to 4 (with four being the most positive response). The resulting values are summed and multiplied by 2.5 to convert the SUS Score range from 0 to 100 (see reference 48).

Table 3: System Usability Scale Scores for MyEnergyBalance website

Item Number	Question	Mean ± SD
1	I think that I would like to use this website frequently.	2.3 ± 1.1
2	I found the website unnecessarily complex.	3.3 ± 1.3
3	I thought the website was easy to use.	3.6 ± 1.2
4	I think that I would need support of a technical person to be able to use this website.	4.8 ± 0.4
5	I found the various functions of this website were well-integrated.	3.6 ± 1.1
6	I thought there was too much inconsistency in this website.	4.0 ± 1.2
7	I would imagine that most people would learn to use this website very quickly.	4.0 ± 0.8
8	I found the website very cumbersome to use.	3.2 ± 1.6
9	I felt confident using this website.	4.4 ± 1.0
10	I needed to learn a lot of things before I could get going with this website.	4.6 ± 0.7
SUS Score^a		69.5 ± 18.7
11	Overall, I would rate the rate the user-friendliness of this website as:	4.6 ± 0.8

Items 1-10: Based on a 5-point Likert Scale (1=Strongly Agree to 5 = Strongly Disagree).

Item 11: Scale based on 7-point Likert scale (1=Worst Imaginable to 7=Best Imaginable)

^aThe SUS Score was calculated by taking the odd numbered items (for Items 1-10) and subtracting one from the user response, and taking the even numbered items and subtracting the user response from five. This scales all values from 0 to 4 (with four being the most positive response). The resulting values are summed and multiplied by 2.5 to convert the SUS Score range from 0 to 100 (see reference 48).

Figure 1: Homepage Menu of the MyEnergyBalance app

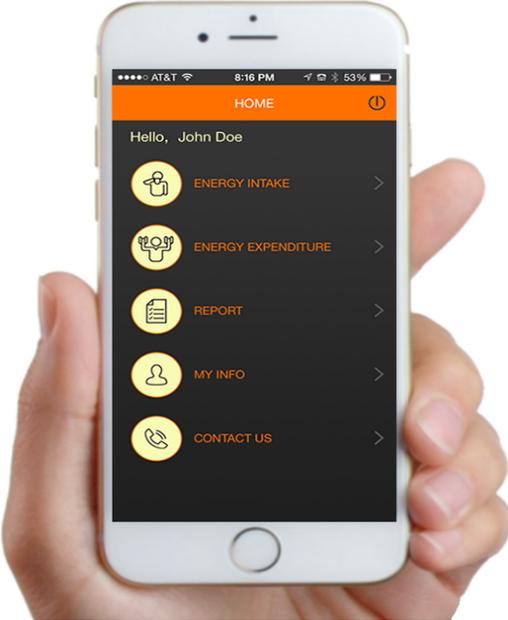


Figure 2: Experimental Design Flow Diagram

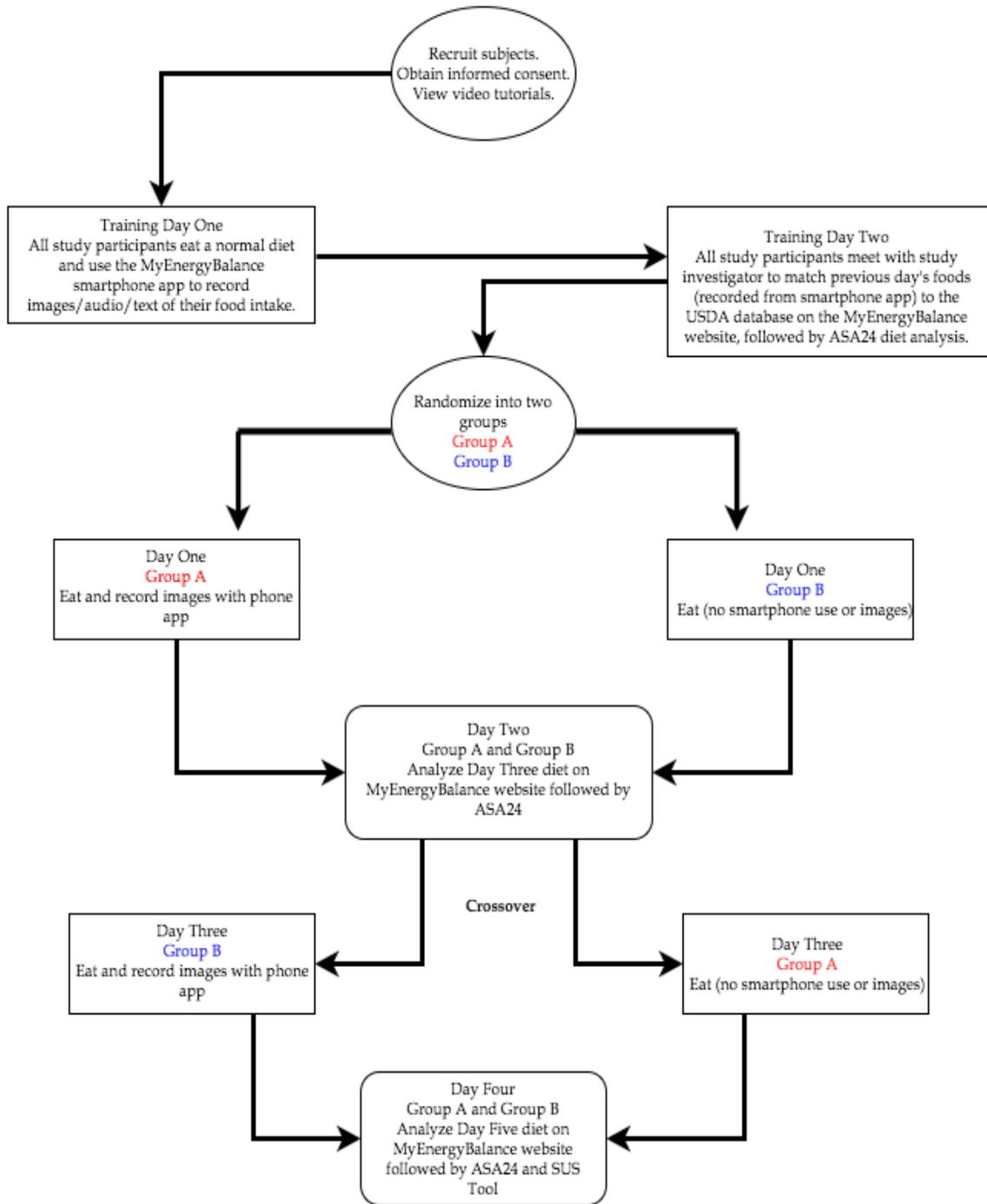


Figure 3: Scatter plot of individual system usability scale scores of the MyEnergyBalance app and the absolute difference in energy intake (kcal) between the MyEnergyBalance app and ASA24 recall (with all subjects)

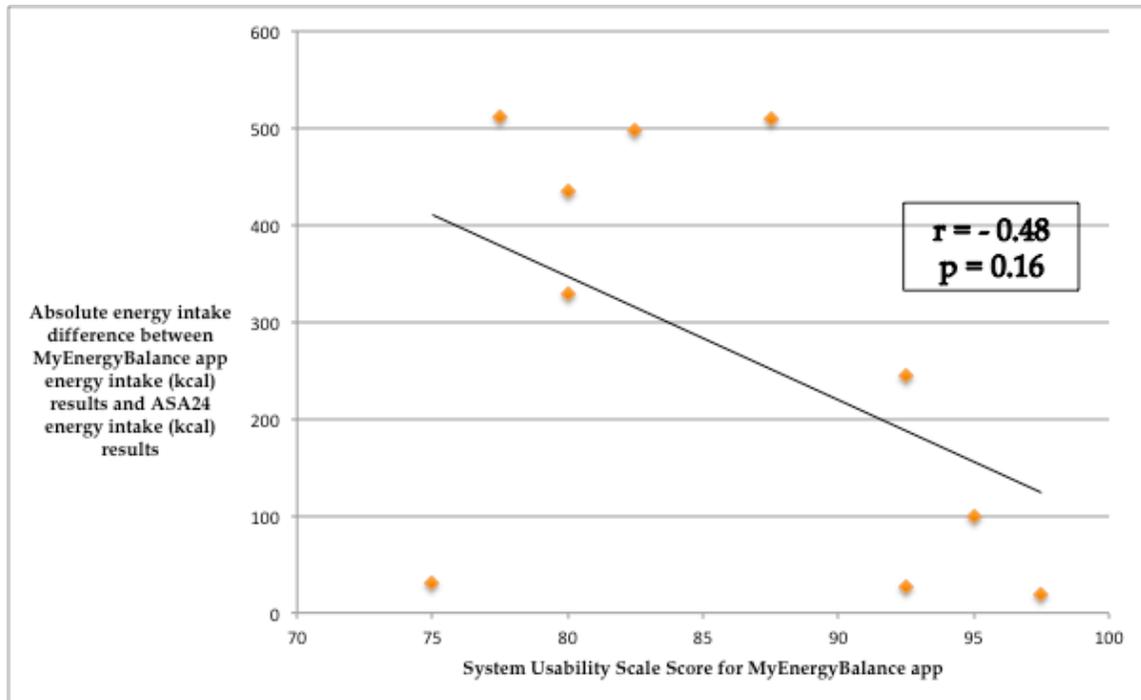


Figure 4: Scatter plot of individual system usability scale scores of the MyEnergyBalance app and the absolute difference in energy intake (kcal) between the MyEnergyBalance app and ASA24 recall (without outlier)

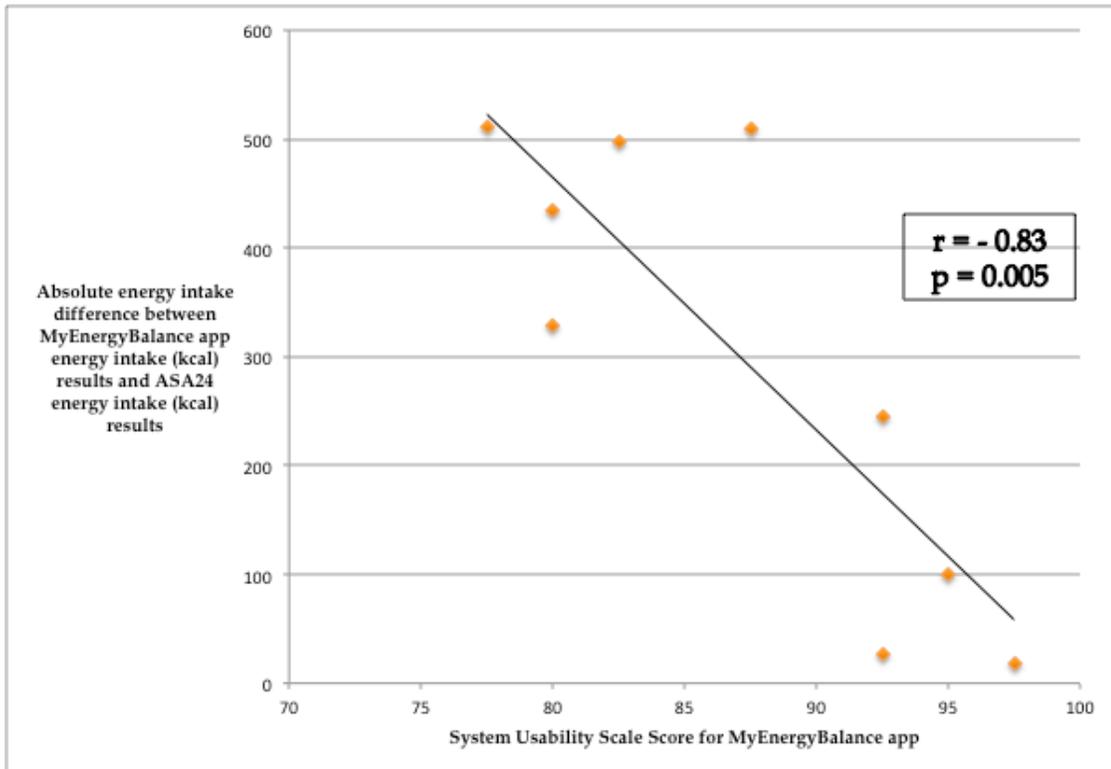


Figure 5: Scatter plot of individual system usability scale scores of the MyEnergyBalance website and the absolute difference in energy intake (kcal) between the MyEnergyBalance website and ASA24 recall (with all subjects)

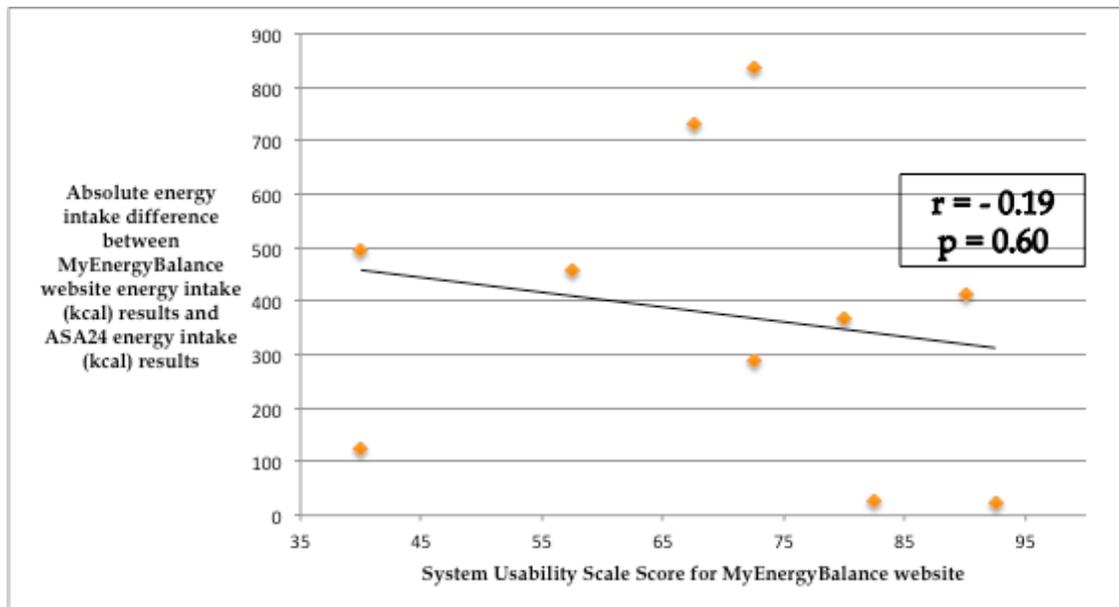
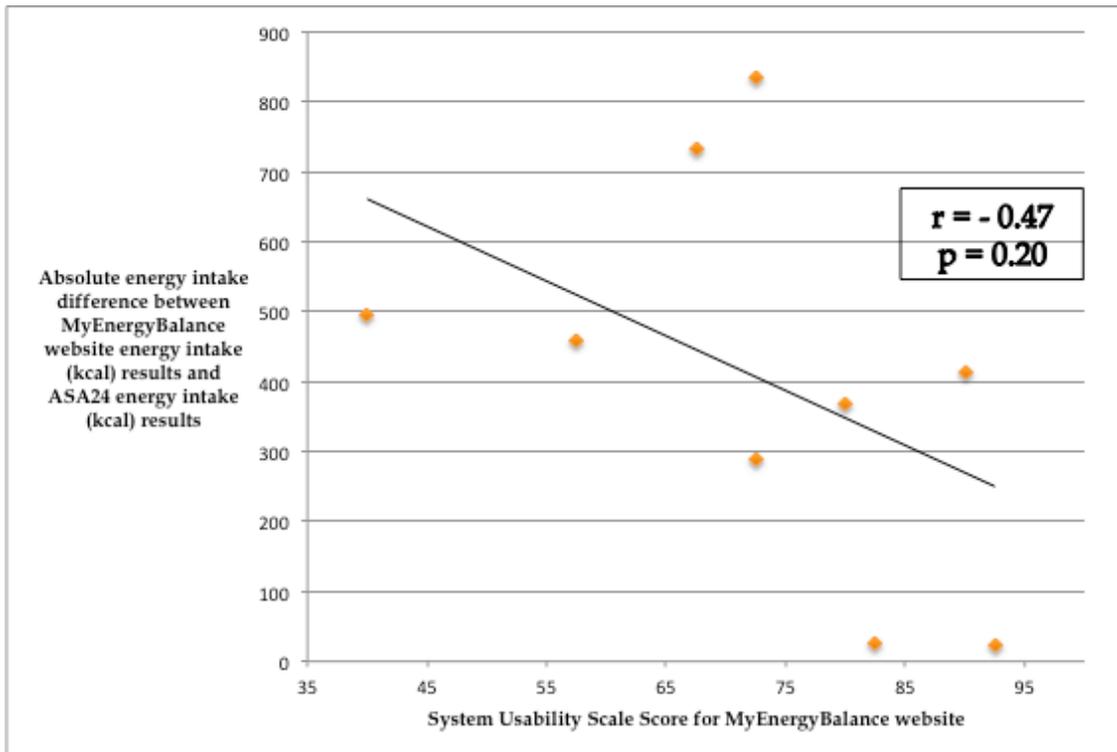


Figure 6: Scatter plot of individual system usability scale scores of the MyEnergyBalance website and the absolute difference in energy intake (kcal) between the MyEnergyBalance website and ASA24 recall (without outlier)



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