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BEHAVIOR CHANGE TECHNIQUES AND MHEALTH INTERVENTIONS FOR OBESITY MANAGEMENT AND WEIGHT LOSS: A NARRATIVE REVIEW AND CASE STUDY OF NOOM

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ABSTRACT

Obesity poses a growing mortality, disability, financial, and environmental burden for a large fraction of the world's population. This multifaceted problem has led to a wide array of weight-loss management techniques which include nutrition and physical activity modification, pharmacotherapy interventions, bariatric surgery, and behavioral interventions. While moderate success has been shown in some weight management techniques, a comprehensive behavioral intervention is a critical component to maintaining weight loss according to the AHA, ACC, NIH, CDC, and WHO. Successful behavioral interventions for weight loss include cognitive behavioral therapy, motivational interviewing, self-monitoring, and group therapy. However, these interventions are often time-intensive and require trained health professionals which can be costly and unscalable to address the obesity pandemic. Mobile health (mHealth) weight loss behavioral interventions have emerged as a promising solution, as they allow individuals to receive treatment and support through mobile devices. This delivery mode reduces the need for in-person appointments and enables remote monitoring and personalized coaching. Furthermore, mHealth interventions have shown to be effective in promoting weight loss, improving dietary habits, increasing physical activity, and enhancing self-management skills, all of which are critical components for long-term weight management success. As the prevalence of obesity continues to rise, mHealth interventions could play a critical role in addressing this growing burden by providing accessible and effective behavioral interventions that can be scaled to reach large populations in need. This thesis reviews the rise in mHealth interventions for weight loss management in overweight and obese populations, as well as a content analysis and quality assessment of Noom, the leading mHealth weight loss intervention on the public market.

TABLE OF CONTENTS

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Chapter 1 : Understanding Overweight and Obesity: Causes, Consequences, and Management Approaches

Introduction

Chapter 1 Synopsis

Since the 1970s, the United States has undergone a significant transformation in its food and physical activity landscape, resulting in a surge in the prevalence of overweight and obesity. With no sign of this trend slowing down, we are continuing to face a global public health emergency that demands immediate attention. This chapter will overview the multifaceted burden of obesity and overweight populations by providing the irrefutable demographic evidence as well as the disease risk factors that contribute to the higher all-cause mortality that this population faces. The biological reason behind weight gain, which is typically the dysregulation of leptin and gremlin, can also be attributed to genetics, and epigenetic traits. The set-point theory provides an explanation as to why weight loss attempts fail, and the importance of gradual weight loss over a longer period of time. In addition, individuals with this condition face increased psychological and sociological impacts that pose threats to their mental health. At a population level, overweight and obese individuals also pose a tremendous burden on healthcare spending and services, as well as tremendous indirect costs related to disability, workers compensation, absenteeism, and presenteeism. At a global level, overweight and obese individuals also contribute significantly more greenhouse gasses to support their lifestyle. Despite widespread impacts that this condition has on our population, public health efforts have shown to be cost effective in the literature, yet significant actions to prevent this pandemic have fallen short.

The chapter will also review the approaches to weight-loss management, which is clinically significant if individuals lose at least 5% to 10% of their baseline weight. There are several effective ways for individuals to reach this target weight loss. Nutritional and physical activity guidelines have suggested for decades that in order to lose weight, individuals must consume nutrient-dense foods with low-calorie density, reduce overall fat and refined/processed sugars consumption. Paired with increased physical activity, specifically 150 minutes of moderate activity, 75 minutes of vigorous activity, and two days of strength training, obese and overweight individuals will reach a negative energy balance, and therefore lose weight. While these recommendations are widely accepted and promoted by public health initiatives, implementation of these guidelines are challenging because of socio-economic factors, food availability and affordability, and the lack of physical activity incorporated in their daily lifestyles. Pharmacotherapy treatments may show potential, yet they come at a cost, including detrimental side-effects, and their safety has not been studied for long-term use. Bariatric surgery is the most effective weight loss strategy, however, this intervention can only serve the most severe individuals. According to most prominent organizations in public health and healthcare research, targeting the behavior that led to weight gain should be the center of all weight loss interventions. The chapter provides a review of effective behavioral interventions, and further breaks down the techniques that have shown effective weight loss success. These techniques include cognitive-behavioral therapy, motivational interviewing, self-monitoring, and group therapy. While they all provide evidence of stand-alone success, they also are costly, time intensive, and require trained healthcare professionals during our current nationwide shortage.

This chapter suggests that advancements in mobile technology may provide a scalable behavioral intervention solution to address the overweight and obesity pandemic.

The Multi-Faceted Burden of Obesity

The National Health and Nutrition Examination Survey (NHANES) reported that in their 2017 to 2020 survey, 30.7% of adults over 20 years old were overweight, 42.4% were obese, and 9.2% had severe obesity. The number of individuals with obesity has been increasing roughly 8% every decade since the 1970s, and current literature suggests that this trend is not slowing down. By 2030, obesity is predicted to rise to 48.9%, and severe obesity will rise to 24.2%. This trend is concerning as obesity is associated with health complications and has become a major public health issue worldwide. This section will first provide statistical evidence surrounding the demographics of the overweight and obesity pandemic, specifically noting the beginning of the growth, and the current projections in the United States and worldwide. An overview of the weight-related disease morbidity and mortality will include evidence that individuals who are overweight and obese have higher all-cause mortality. This condition not only affects physical health, but also causes psychological and sociological impacts including social stigma, discrimination, and negative self-image. Finally, this section will include the economic and environmental impacts that obesity and overweight individuals have on society as a whole. Understanding the multifaceted impacts that this condition has is important for motivating governmental leaders, public health officials and scientific researchers to develop effective prevention and management strategies for the general population.

Overweight and Obesity Demographics

The prevalence of obesity continues to rise in the United States and worldwide, leading to a costly pandemic in both developing and developed nations. The prevalence of BMI-defined obesity in adults in the United States has been widely studied as it is a pressing issue for our nation's public health. As defined by the NHANES, BMI (calculated as weight in kilograms divided by height in meters squared) of 25.0 to <30 kg/m^2 falls within the overweight range and BMIs of 30.0 or higher fall within the obesity range. Obesity is then subdivided into three categories: Class 1: BMI of 30 to < 35, Class 2: BMI of 35 to < 40, and Class 3: BMI of 40 or higher. Class 3 obesity is categorized as "severe" obesity. Studies that examined the trends from the NHANES cross-sectional nationally representative samples show a clear escalation of the overweight and obesity pandemic in the United States.

As previously mentioned, According to the National Institutes of Health (NIH) from the NHANES, in 2017-2020, 30.7% of adults over 20 years old were overweight, 42.4% were obese, and 9.2% had severe obesity (Fryar, 2020). These demographic statistics follow a national trend of significant increases in prevalence since the 1970s. In the 1960s, 13% of U.S. adults were obese (May et al., 2013). There was little change in obesity statistics from 1960-1962 through 1971-1974. The US experienced a significant increase of 8% (14.5% to 22.5%) from 1976-1980 through 1988-1994. This trend was followed by a similar increase of 7.6% between the 1988-1994 and 1999-2000 surveys (22.9% to 30.5%) (Legal et al., 1998). From the 1999-2000 cohort through the 2017-2020 cohort, US obesity prevalence has increased from 30.5% to 41.9%, and severe obesity increased from 4.7% to 9.2% (NHANES, 2021). Current obesity projections in the

United States find that by 2030, obesity will rise to 48.9%, and severe obesity will rise to 24.2% (Vasa et al., 2005; Ward et al., 2019).

The trends in the United States are congruent with global trends. A systematic review of surveys, reports, and published studies (n=1769) from 1980 to 2013 found that worldwide, the proportion of adults who are overweight and obese had increased from 28.8% to 36.9% in men and from 29.8% to 38% in women (Ng et al., 2014). Finucane et al. (2011) reviewed obesity trends from 1980 to 2008 and found that obesity increased from 4.8% to 9.8% in men and from 7.9% to 13.8% in women. The 2023 World Obesity Atlas reported that 51% of the global population will be overweight and obese within 12 years (2035) if prevention, treatment, and support do not improve (World Obesity Federation, 2023).

This pandemic leads to a tremendous burden of disease. In 2010 alone, overweight and obesity were estimated to cause 3.4 million deaths, 3.9% of years of life lost, and 3.8% of disability-adjusted life-years (DALYs) worldwide (Ng et al., 2014). The rapidly growing population of overweight and obese individuals is considered a global pandemic by the World Health Organization (WHO) (Boutari et al., 2022). As our world continues to become increasingly overweight and obese, it is essential to address the widespread effects that obesity and overweight populations have on their health and the global economy.

Weight-Related Health Complications

As overweight and obesity prevalence continues to rise, so have obesity-related diseases. Individuals who are overweight and obese have an increased risk of heart disease, stroke, type 2 diabetes, and certain types of cancer, including breast, bowel, pancreatic, kidney, and colorectal cancer (CDC, 2022). In the United States, obese men have a sevenfold higher risk of developing type 2 diabetes, while obese women have a 12-fold risk (Guh et al., 2009). Overweight individuals have a 32% higher risk of developing coronary artery disease (CAD), while obese individuals have an 81% higher risk (Bogers et al., 2007). Ischemic stroke increased in overweight populations by 22% and in obese populations by 64% (Strazzullo et al., 2010). Cardiovascular death in obese women is 63% higher from CAD, and 53% higher risk from any type of cardiovascular disease; men had similarly elevated risks (McGee et al., 2005). In addition to the evidence, a further systematic analysis found that a higher BMI is associated with higher all-cause mortality (Gonzalez et al., 2010).

At a global level, the Global VMI Mortality Collaboration of over 500 investigators from 32 countries agreed on an analysis plan to produce reliable estimates of potentially causal associations of overweight and obesity with mortality. Analysis of data from 4 million adults (combining 189 studies) found that for each 5-unit increase in BMI above 25 kg/m2, the corresponding increases in risk were 49% for cardiovascular mortality, 38% for respiratory disease mortality, and 19% for cancer mortality (Global BMI Mortality Collaboration, 2016). Being overweight or obese poses a tremendous risk to the health of these individuals. Not only does it affect their physical health, but it is also detrimental to their general well-being.

Biological Underpinnings

There are several biological underpinnings that are important to discuss when understanding the multi-faceted nature of obesity. Negative feedback loops play an important role in regulating appetite and maintaining energy balance in the body. These feedback loops involve multiple hormones that communicate between the brain, gut, and other organs to signal hunger and fullness. When individuals eat, hormones like leptin and insulin are released, which signal the brain to reduce appetite and increase metabolism. When individuals reduce caloric intake, the hormone ghrelin is released which signals the brain to increase appetite and reduce metabolism. When individuals eat, leptin inhibits the release of ghrelin, therefore reducing the hunger signals in the brain. In overweight and obese individuals, the circulating level of leptin is increased, and the level of ghrelin is decreased. Scientific literature has now established that obese patients tend to be leptin-resistant. Leptin resistance can cause increased hunger and decreased energy expenditure. This cycle contributes to continued weight gain (Mayers et al., 2010).

Genetics has also been shown to play a significant role in obesity. While there is no single genetic cause that has been identified to cause obesity, about 50 genes have been associated with obesity, most with very small effects (Herrera et al., 2011). Obesity is more likely to occur in families with a clear inheritance pattern caused by the MC4R gene which encodes for the melanocortin 4 receptor. Mutations in the MC4R gene are found in a small fraction (<5%) of obese people. The effect of this mutation includes increased hunger which leads to overeating (Herrera et al., 2011). Numerous epigenetic mechanisms have been implicated in diet-induced obesity. For example, the LINE-1 gene is found linked with increased expression in women who consume high-fat meals versus those who follow healthy dietary patterns (Mahmoud et al., 2022). Epigenetic traits have been linked to dietary patterns in obese populations, which highlights the importance of environmental influences on obesity.

This review will address the biological mechanisms that contribute to the challenges faced by individuals with obesity when trying to achieve weight loss. The set-point theory proposes that the body tries to maintain its weight within a preferred range which develops from the complex interplay between genetics and the environment (Farias et al., 2011). Several studies have shown that body weight is maintained at a stable range despite the variability in energy intake and expenditure. For example, if a person’s weight falls below this range, the body responds by increasing appetite and reducing energy expenditure, and when the weight goes above this range, the opposite response occurs. The set point is suggested to be influenced by the hypothalamus and its regulation of leptin and ghrelin as well as the genetic and environmental makeup of an individual (Speakman et al., 2011). Despite this, the literature suggests that this set point can be overcome. First, individuals need to consider the time it takes to change this set point. For optimal adaptation of the body’s systems to new circumstances, it is recommended to lose weight gradually over an extended period of time. Physical activity and dietary recommendations should be followed strictly, and individuals who are attempting to lose weight need to be adherent to these rules (Muller et al., 2010). Maintaining a gradual weight loss approach over a long period of time is crucial to overcome the body's set point and preventing the rebound effect, which is commonly observed in rapid weight loss. This further suggests the need for a support team to motivate the individual to stay on track during their weight loss journey.

Psychological and Sociological Impacts

Being obese or overweight can have significant sociological and psychological impacts on an individual. These impacts may include social stigma, discrimination, and negative self-image. This population is often blamed for their weight, with the common perception that weight stigmatization is justifiable as it may lead these individuals to adopt healthier behaviors. Stigmatizing individuals due to their weight not only hinders practical efforts to address obesity but also creates health disparities and threatens their overall health. Weight stigmatization in both a clinical and nonclinical setting is a significant risk factor for depression, low self-esteem, and body dissatisfaction (Puhl, 2010). These findings are supported by a study from the National Epidemiological Survey on Alcohol and Related Conditions (NEARC), which examined these effects on more than 9,000 obese adults. The findings found that perceived weight discrimination was significantly associated with a current diagnosis of mood and anxiety disorders for mental health services, even when controlling for socio-demographic characteristics and perceived stress (Hatzenbuehler et al., 2009). One study estimates a 25% increase in odds of mood and anxiety disorders among obese individuals (Simon et al., 2006). It is essential to recognize the harmful impact of weight stigmatization on both the physical and mental health of individuals who are overweight or obese and to work towards creating a society that supports and empowers individuals to make healthy choices without shame or discrimination.

Economic and Environmental Impacts

The impact of 1.3 billion people who are overweight and obese also has a widespread toll on our global economy. This impact includes increased healthcare costs, decreased productivity, and an environmental impact. Further studies will examine these effects in the United States alone. The economic impact that overweight and obese populations have in the US is inherently challenging to examine due to the direct and indirect costs related to the condition. Some direct costs of individuals who are overweight or obese include higher healthcare costs than those who are at a healthy weight. One estimate found that the direct medical cost of overweight and obesity combined is approximately 5% to 10% of U.S. healthcare spending (Tsai et al., 2011). In adults, obesity is associated with $1,861 in excess annual medical costs per person, accounting for 172.78 billion dollars of annual healthcare expenditures in 2019 (Ward et al., 2021). The substantial economic burden on our healthcare system also tremendously burdens our practitioners in an already strained system.

Indirect costs typically include the costs related to disability, workers' compensation, absenteeism, and presenteeism (reduction in productivity while at work). A systematic review of the indirect costs of obesity (n=50) found that the evidence predominantly confirms substantial short-term and long-term indirect costs of overweight and obesity due to lost productivity, especially absenteeism and presenteeism, contributing to high indirect costs (Goettler, 2017). Indirect costs are a multifaceted problem, therefore, direct estimates of the economic cost still need to be discovered.

In addition to economic costs, this population profoundly impacts metabolic food waste, which receives little attention in the scientific community. Individuals who consume more significant quantities of food and beverages require more to be produced and transported to them, which increases greenhouse gas emissions. This population also requires more consumption of fossil fuels to transport them as well as emits more carbon dioxide compared to those of average weight. Preliminary studies have attempted to measure the overall impact that this population has on greenhouse gasses. One study claimed that overweight and obese individuals emit 20% more greenhouse gas emissions (carbon dioxide, methane, and nitrous oxide) than those at an average weight (Magkos et al., 2019). As the world confronts our greenhouse gas emissions linked to global warming and climate change, research needs to further examine the impact of overconsumption on our world.

The burden of obesity is multifaceted, encompassing medical, economic, psychological, sociological, and environmental factors. As overweight and obesity rates continue to rise, the prevalence of obesity-related conditions increases, leading to higher risks of chronic diseases and mortality. Moreover, individuals who are overweight or obese may face stigmatization, discrimination, and negative self-image, leading to significant psychological and sociological impacts. This population's impact on the global economy is substantial, with increased healthcare costs, decreased productivity, and environmental impact.

With tremendous economic, sociological, psychological, healthcare, and environmental costs associated with being overweight and obese, effective policies to promote weight loss would have tremendous economic benefits that are difficult to precisely estimate due to the diverse and complex effects that this problem has on our system. Despite the toll this disease has on our populations, the obesity pandemic has not slowed. This next section will overview common approaches to weight-loss management that have been utilized to slow down this pandemic.

Approaches to Weight-Loss Management

Clinically significant weight loss is defined as at least a 5% to 10% reduction in weight from the baseline level. Maintenance of this weight loss is associated with improvements in cardiometabolic risk factors, including lipid profile, insulin sensitivity, and high blood pressure. Prevention of diabetes starts at 3% weight loss, while diabetes remission typically requires 10 to

15% weight loss (Garvey et al., 2016). The Global BMI Mortality Collaboration (2016) recommended that individuals who are overweight and obese should attempt to achieve at least a BMI of 20.0- 25.0 kg/m2 to minimize all-cause mortality linked to these conditions. The following section will provide evidence supporting the cost-effectiveness of the public health campaigns as well as a call to action for more public health interventions and research surrounding their effectiveness. This section will also overview the clinically recommended modifications in nutrition and physical activity that are essential to weight loss, and how these recommendations translate from the ivory tower to the general population. A review of the pharmacotherapy methods will provide evidence that some medications promote weight loss, however, their safety has not been tested for long term use. While bariatric surgery is the most successful weight loss intervention, only individuals who have a BMI >35 kg/m2 are eligible candidates for this surgery. Finally, this section will review behavioral interventions for weight loss which are widely recommended to be at the center of any weight loss management approach. A further review of the successful behavioral intervention techniques used in weight loss will be provided in the following section.

Cost-Effectiveness of Public Health Campaigns

Public health efforts to combat obesity are essential to address this significant public health issue. These efforts include education and awareness campaigns, community-based interventions, policy changes, and regulation. A comprehensive and collaborative approach is necessary to combat the burden of obesity effectively. Effective obesity programs have been proven to have tremendous returns on investment, primarily when they target childhood obesity.

Childhood obesity affects 19.7% of children aged 2-19, nearly quadrupling from 5% in 1974 (May et al., 2013; NHANES, 2021). Encouraging healthy habits during childhood through public health interventions offers the most cost-effective tactics for preventing obesity. Addressing obesity in adults is more challenging than modifying lifestyle choices earlier in life (Pandita et al., 2016). To address this issue, CHOICES (Cost Effectiveness of Childhood Obesity Interventions) is a Harvard Public Health study to compare the outcomes of policies and programs over ten years (2015-2025), which will provide insight into how to target childhood obesity cost-effectively (Gortmaker et al., 2015). A community weight loss intervention simulation using a state-transition Markov model estimated the lifetime costs of participants. The study found that for every $1 spent on the internet intervention program, ROI was $16.70 in reduced medical costs (Michaud et al., 2017). The cost-effectiveness of weight loss interventions is complex to measure. Regardless, system-wide investments to improve weight loss may be financially advantageous if they are effective at obesity prevention. This narrative review calls for widespread public health campaigns and research behind the cost-effectiveness of these interventions.

Nutritional Guidelines

Nutritional interventions for weight-loss maintenance have often targeted energy balance and dietary recommendations. Energy balance is the state achieved when energy intake equals energy expenditure. Humans take in energy through their diet and expend it through the resting metabolic rate (RMR) and the thermic effect of food (TEF) and activity. When the body is in energy balance, body weight is stable, however, if food intake exceeds the RMR and TEF and activity, individuals will experience a positive energy balance which results in weight gain, with 60-80% of the resulting weight gain attributable to body fat (Hill et al., 2013). Nutritional diets often promote consuming nutrient-dense foods with low-calorie density to cause a negative energy balance. A meta-analysis of weight loss among named diet programs in overweight and obese adults highlighted the outcomes based on the diet class (micronutrient composition) and named diet. Among the 59 eligible articles with 48 randomized trials, the results found that significant weight loss was observed with any low-carbohydrate or low-fat diet over 12 months. The findings also indicated that behavioral support and exercise enhanced weight loss (Johnston et al., 2014). Another systematic review of popular weight loss strategies (juicing or detoxification diets, intermittent fasting, the paleo diet, and high-intensity training) found similar findings. The conclusion made was that some fad diets and exercise plans do lead to weight loss, however, they are all based on the concept of caloric restriction (Obert et al., 2017). In theory, nutritional interventions that promote energy balance and the consumption of nutrient-dense, low-calorie foods are effective for weight-loss maintenance. However, adherence to such diets is extremely difficult over the long term, and weight loss is often enhanced by additional behavioral support and exercise (Rolls et al., 2000).

The American Heart Association (AHA), the NIH, and the WHO have been providing clear guidelines on weight loss strategies since the emergence of obesity prevalence. In 1977, the first edition of the “Dietary Goals for the United States," published by the Senate Select Committee on Nutrition and Human Needs, highlighted critical interventions to tackle this issue. This report called for Americans to reduce their overall fat consumption, saturated fat consumption, refined and processed sugars and cholesterol, and to increase their consumption of fruits, vegetables, and whole grains (Ebbeling et al., 2012). While the content of the review does not reflect current scientific knowledge, a similar message is reflected in the 2020-2025 Dietary Guidelines for Americans. The recent recommendation was to consume more vegetables of all types, fruits, whole grains, limit foods and beverages high in added sugars, saturated fat, and sodium (Snetselaar et al., 2021). Despite the congruences in the messaging, obesity prevalence has increased from 14.5% in 1971 to 42.4% in 2017. The worsening obesity pandemic points to a failure to implement the recommended strategies. While current nutrition weight-loss studies show sustained weight loss, these strategies have failed to be implemented nationally. Dietary guidelines alone could guide obese and overweight individuals toward losing weight. Beneficial guidelines may be simple in theory but difficult in practice.

Physical Activity Guidelines

As previously stated, changing nutritional habits as well as increasing physical activity is crucial for weight-loss maintenance. This recommendation has existed for a long time, even Hippocrates stated, “Eating alone will not keep a man well, he must also take exercise” (Hippocrates, 400 BC). Early recommendations from the American Hospital Association (AHA) from 1972 to 1990 were primarily based on endurance exercise to enhance performance, especially aerobic capacity. This recommendation was modified in the late 90s to include aerobic and anaerobic exercises. In 2023, the Centers for Disease Control (CDC) recommends an average of 150 minutes of moderate activity each week and 75 minutes of vigorous-intensity aerobic activities. This recommendation also includes two or more days of strength training (CDC, 2023). These recommendations address the positive energy balance in overweight and obese individuals who are sedentary. These recommendations also apply to individuals who are at a normal weight and want to maintain their health. Studies examining weight loss through increased physical activity were typically measured by pedometers. A systematic review found that even when obese populations increase their daily steps to recommended levels, the weight loss was modest (averaging about 2kg), and minimal changes were found in biomarker risk factors for cardiovascular disease (Swift et al., 2014). These further suggest that physical activity alone is not enough for most people to lose weight because of the comprehensive approach to weight loss and health which needs to include healthy eating and other lifestyle changes (Wharton et al., 2020).

Pharmacotherapy Treatments

Pharmacotherapy is often used as a comprehensive patient-centered approach to address the chronic diseases that arise in overweight and obese populations. Treatment includes blood pressure-reducing, lipid-lowering, glucose-lowering, and diabetes medications. These interventions can significantly reduce the morbidity and mortality of diseases that may arise in overweight and obese populations. Unfortunately, for those using medication to manage their chronic illness, 50% of drugs are not taken as prescribed (Kini et al., 2018). Some medications have been found to induce weight loss as a side effect of the desired effect. Weight loss was most notably found in randomized trials when studying the effects of metformin (1.1 kg), pramlintide (2.3 kg), zonisamide (7.7 kg), and topiramate (3.8 kg) (Domecq et al., 2015). Technological pharmaceutical advancements have led to increased medication use that can promote weight loss. While the medications differ in the mechanism of action, some make it harder for your body to absorb fat, while others make you feel less hungry or full sooner. The NIH provided a list of weight management medications which included Xenical, Alli, Qsymia, Contrave, Saxenda, Wegovy, and phentermine. The NIH also notes that in some cases, the side effects of prescription medications that treat overweight and obesity may outweigh the benefits and cause severe illness. In addition, these medications are largely not tested for long-term use, and their safety is relatively unknown (Yanovski et al., 2014). Medications designed for individuals to lose weight are not a cure-all either. They are meant to be taken with changes in behavior, including healthy eating and increased physical activity.

Bariatric Surgery

One of the most successful methods for weight loss is surgical intervention. In 2018, there were approximately 252,000 bariatric procedures. Typically, these procedures are recommended for individuals with a BMI of 35 or higher. 61% of bariatric procedures are sleeve gastrectomies which are procedures to reduce the stomach to about 15% of its original size so that the stomach cannot hold as much food. 17% of the surgeries are Roux-en-Y Gastric Bypass (RYGB) procedures which reduce the size of the upper stomach to reduce the amount of food an individual can eat (Arterburn et al., 2020). Generally, modern bariatric procedures have strong evidence of efficacy and safety. While there is limited evidence of the durability of weight loss compared with nonsurgical matches across bariatric procedures, a 10-year weight change study of 1787 veterans highlighted the success of the procedures. RYGB patients lost 21% more baseline weight at ten years than the nonsurgical group. Additionally, RYGB patients had higher rates of weight loss, with 71.8% having more than 20% estimated weight loss and 39.7% having more than 30% estimated weight loss at ten years (Maciejewski et al., 2016). The benefits of bariatric surgeries affect weight loss and the disease complications that arise in obese populations. Systematic reviews indicate that bariatric surgery is associated with a 1-year hypertension remission rate from 43% to 83% (Climent, 2020). Bariatric surgery is linked to a decreased risk of all types of cancer and obesity-related cancers, according to data from 8 observational studies involving 635,642 patients (Arterburn et al., 2020). High-quality evidence shows that bariatric surgery can improve type 2 diabetes outcomes, according to 12 randomized controlled trials, including 874 patients comparing surgical to medical therapy and varying size, follow-up, and procedures used (Arterburn et al., 2020). The review also highlights how surgery can reduce sleep apnea and dyslipidemia rates in this population (Arterburn et al., 2020).

The benefits of bariatric surgery suggest that this weight loss method is the most effective for both short and long-term effects. This strategy is only recommended for the morbidly obese (BMI > 35 kg/m2). With over a quarter million receiving this surgery annually, over 137 million people are still obese, meaning that most individuals will never have access to this weight loss strategy. Meanwhile, the United States is currently experiencing a major physician shortage. The Association of American Medical Colleges (AAMC) predicts a shortage of 54,100 to 139,000 by 2034, including shortages in specialties like bariatric surgeons (AAMC Report, 2021). As our population continues to grow in weight and number, bariatric surgeries will only help a small fraction of the overweight and obese population in the future. This weight loss method is not scalable to fully address the majority of the pandemic in the United States.

Behavioral Interventions

As previously discussed, nutritional and physical activity modifications, pharmacotherapy, and bariatric surgery all have limitations in achieving long-term weight loss. These methods are most effective if the individual is motivated to change the behaviors that contributed to their weight gain. The physical, biological, psychological, and social behaviors contributing to weight gain must be understood by the individual and changed through behavioral interventions. Behavioral interventions provide a holistic approach that emphasizes the establishment of new healthy habits which contribute to a long-term gradual weight loss approach. Customizing these interventions to match each individual's barriers to behavior change is important to ensure success in maintaining long-term weight loss (Wadden et al., 2012).

It is important to note that lifestyle modification, behavioral treatment, and behavioral weight control are frequently used interchangeably in the literature. They all involve the same three fundamental aspects of weight loss interventions: diet, exercise, and behavior therapy. Research has highlighted specific behavior interventions that have been shown to increase weight loss success. This includes regular self-monitoring, goal-setting, reducing calorie intake, increasing physical activity, eating smaller and more frequent meals, consistently having breakfast, cooking at home more often, reducing screen time, and using portion-controlled meals or meal substitutes (Hall et al., 2018). These recommendations are often provided by trained therapists, certified health coaches, dietitians, physical therapists, and other healthcare professionals through consistent treatment appointments and assigned take home tasks (Wadden et al., 2012).

For an individual to be motivated to change their lifestyle, it is important to address the psychological and sociological influences contributing to healthy behavior change. Behavioral interventions can cause an improvement of psychological and social outcomes, such as positive self-image, improved self-efficacy, and reduced stigma associated with obesity (Puhl et al., 2010). Behavioral interventions to combat obesity are widely supported by the American Heart Association (AHA), American College of Cardiology (ACC), NIH, CDC, and WHO. The following section provides an overview of behavioral interventions for obesity management and highlight the evidenced-based features that should be included in all in-person behavioral interventions.

Evidence-Based Behavioral Interventions

According to national and international health organizations, behavioral interventions are suggested to be the primary target for managing the obesity pandemic. To address the rising CVD rates due to the obesity and overweight pandemic, the "2019 ACC/AHA Guideline on the Primary Prevention of Cardiovascular Disease: A Report of the American College of Cardiology/American Heart Association Task Force on Clinical Practice Guidelines" provided scientific evidence for clinical practice guidelines with recommendations to improve cardiovascular health. The guidelines provided the top 10 take-home messages for the primary prevention of cardiovascular disease. The first take-home message stated, "The most important way to prevent atherosclerotic vascular disease, heart failure, and atrial fibrillation is to promote a healthy lifestyle throughout life." Statements made by the WHO also reflect this emphasis on promoting a healthy lifestyle throughout life. According to the WHO, 80% of all cardiovascular disease mortality may be prevented with adequate lifestyle changes, including a healthy diet, regular physical activity, and not using tobacco products (WHO, 2022). Prominent organizations in public health and healthcare research agree that behavioral interventions are a pivotal aspect in promoting healthy lifestyle changes and reducing the risk of chronic diseases related to obesity. To understand the efficacy of these interventions, this narrative review will provide two landmark studies, the Diabetes Prevention Program (DPP) and the Look AHEAD study, which specifically targeted weight loss in individuals with type 2 diabetes. These interventions provide the basis of the features needed for successful behavioral intervention. The following sections will include the evidence-based methods that have been utilized to address behavior change including cognitive behavioral therapy, motivational interviewing, self-monitoring, and group therapy. While these techniques are often successful, they are also time-consuming, comprehensive, costly, and unscalable to the general population.

Landmark Behavioral Interventions

Obesity is a major risk factor for type 2 diabetes, with roughly 30 percent of overweight people having the disease, and 85 percent of diabetics are overweight (Powel, 2019). To address this, The DPP was a randomized clinical study conducted by the National Institutes of Health (NIH) to determine whether lifestyle changes or medication (metformin) can prevent or delay the onset of type 2 diabetes in high-risk individuals. The intervention group received intensive coaching from “lifestyle coaches” to achieve and maintain a minimal 7% weight loss through the program's key features, which included: education on behavioral self-management strategies for weight loss and physical activity, supervised physical activity sessions, group and individual counseling, tailoring the intervention to the individual, healthy eating interventions, and frequent contact with participants. During the 16 sessions over 24 weeks, they received frequent feedback and support to help them stay motivated and make sustainable lifestyle changes. After a 3-year follow-up, the lifestyle intervention showed a 58% decrease in the incidence of type 2 diabetes compared to the 31% decrease in the metformin-treated group (DPPOS, 2002). The Diabetes Prevention Program Outcomes Study (DDPOS) has followed most DPP participants since 2002, showing that the lifestyle intervention group and those taking metformin continue to prevent or delay type 2 diabetes for at least 15 years (DPPRG, 2015).

The Look AHEAD (Action for Health in Diabetes) study was a multicenter randomized controlled trial of 5,145 participants from 2001-2012. It was designed to determine if the effects of intentional weight loss through an intensive lifestyle intervention (ILI) vs. usual care (Diabetes support and education [DSE]) would have an effect on cardiovascular morbidity and mortality in overweight/obese adults with type 2 diabetes. The first year included weekly comprehensive lifestyle interventions designed to lose >7% of their initial weight (Wadden et al., 2006). From years 2-8, the participants had one monthly on-site meeting and a follow-up phone call. After one year, the ILI participants lost a mean of 8.5% of their initial weight compared with 0.6% for DSE. The ultimate finding was that the intervention did not reduce the rate of cardiovascular events between the study groups, however, it did demonstrate significant differences in weight loss and maintenance. At year 8, ILI lost 4.7% of their initial weight compared to 2.1% for the DSE group (Look Ahead Research Group, 2014).

These studies demonstrate that effective behavioral strategies can promote weight loss maintenance and prevent the onset of type 2 diabetes in high-risk individuals. The DPP and the Look AHEAD study utilized intensive coaching, education on behavioral self-management strategies, physical activity interventions, and frequent contact with participants to help them make sustainable lifestyle changes. While the DPP showed a significant reduction in the incidence of type 2 diabetes, the Look AHEAD study found that intensive lifestyle intervention can lead to greater weight loss and maintenance over the long term. The DPP, Look AHEAD, and other landmark behavioral intervention papers differ in how they target the desired behavior. They all use cognitive psychology principles and techniques for modifying diet, exercise, and self-efficacy (Wadden et al., 2004).

Cognitive Behavioral Therapy

Cognitive behavioral therapy interventions for weight loss have been widely studied in clinical settings. Studies examining cognitive behavioral interventions for weight loss are difficult to reproduce due to the variability in the behavioral intervention groups, specifically, the number of sessions, the variability in individualized and group therapy sessions, and the targets of the behavioral intervention (Jacob et al., 2018). While they all differ in the cognitive psychology theories of behavior change, they all address a need for cognitive restructuring. Cognitive restructuring has proven effective in weight loss interventions by helping individuals modify their thought patterns. In this context, the aim is to replace negative or distorted thoughts related to food and body image with more positive and realistic thoughts, which can lead to successful weight management (David et al., 2018).

Cognitive behavioral interventions also address the personal motivations surrounding the desired behavior change. The internal drive that propels an individual towards achieving a particular goal is known as self-efficacy which pertains to an individual's confidence in their ability to carry out the necessary actions to accomplish specific objectives. Individuals with high self-efficacy have the confidence to control their motivation, behavior, and social environment (Bandura et al., 1977). Behavior change theories that address self-efficacy include the Health Belief Model, the Social Cognitive Theory, the Theory of Planned Behavior, and the Self-Determination Theory. While they all address different cognitive schemas, they do provide a framework for the complex process of behavior change and developing effective interventions to promote healthy behaviors.

The literature makes clear distinctions between behavioral therapy and cognitive-behavioral therapy. Cognitive-behavioral therapy for obesity (CBT-OB) is a progressive approach to treating obesity that blends traditional behavioral therapy techniques (e.g., self-monitoring, goal-setting, stimulus control) with customized cognitive strategies (such as skills for increasing social support and problem-solving) (Grave et al., 2020). The CBT-OB model is a recent rendition of behavioral therapy for obesity (BT-OB). BT-OB is a behavioral treatment based on learning theory that primarily focuses on modifying environmental stimuli and consequences of food intake to prompt patients to change their dietary and physical activity habits. CBT-OB, on the other hand, integrates CBT-based strategies and procedures, aiming to produce a cognitive change to influence long-term maintenance of lifestyle modification and personalized cognitive conceptualization to tackle negative weight loss and maintenance mechanisms (Grave et al., 2020). While CBT interventions are highly variable among research trials, systematic reviews can still provide an overview of the efficacy of CBT. A meta-analysis reviewed 12 randomized controlled clinical trials (n=6,805) of weight loss interventions on weight loss and psychological outcomes (eating behaviors, depressive/anxiety symptoms) in overweight or obese adults. The study found that CBT effectively promoted weight loss, increased cognitive restraint, and reduced emotional eating. The study finds that CBT addresses the underlying psychological factors influencing weight loss behaviors (Jacob et al., 2018).

CBT as a weight loss technique also increases adherence to weight loss diets. In a RCT study, a total of 88 patients with morbid obesity were analyzed to evaluate the effectiveness of CBT-OB treatment. The study compared two groups, one following a high-protein diet (HPD) and the other a high-carbohydrate diet (HCD). Attrition rates in the BT-OB control group were above 50%, while the attrition rates for the CBT-OB were 25.6% and 17.8% in the HPD and HCD, respectively, and experienced a weight loss of 15% after 12 months (Dalle Grave et al., 2013). This study highlighted the successes in increasing intervention adherence, however, this program was highly intensive. The program included 15 sessions with CBT groups (5 a week), 18 aerobic exercise sessions, and six calisthenic training sessions for the first three weeks. The 48-week outpatient program included twelve sessions of 45 min over 48 weeks with a dietitian (Dalle Grave et al., 2013).

While these studies provide evidence of the efficacy of CBT intervention for weight loss, the DPP and the Look AHEAD studies also used cognitive behavior techniques to assist in healthy behavior change in overweight and obese diabetic populations. Implementing cognitive behavioral techniques can be time intensive, requires trained professionals to guide these discussions, and is not scalable to a general population.

Motivational Interviewing

A highly individualized behavioral intervention studied in weight loss interventions is called motivational interviewing (MI). MI is a guided communication style designed to empower people by addressing the individual meaning, importance, and capacity for change (Resbucow et al., 2012). Motivational interviewing is based on a set of clinical techniques derived from self-determination theory, a psychological framework that focuses on the motivation behind human behavior (Patrick et al., 2012). MI provides individuals with intrinsic motivation for behavior change, thus building self-efficacy and confidence to change their goals. MI is encouraged to be delivered by the physician but can also be delivered by other healthcare professionals. This client-centered method of intervention focused on enhancing intrinsic motivation and behavior change.

MI differs from CBT by focusing on the individual's motivation to change, while CBT focuses on changing negative thought patterns and behaviors through techniques such as cognitive restructuring. MI techniques can be used within CBT. Without clear guidelines on how researchers implement MI and CBT within behavioral weight-loss interventions, there could be a crossover in these techniques because they both address self-efficacy.

In a systematic review of 24 randomized controlled trials, MI was provided by various clinicians and compared to usual care. Out of the analyzed studies, nine (37.5%) displayed significant weight loss when the MI condition was compared to the control group. Additionally, thirteen studies (54.2%) of patients undergoing MI achieved a minimum of 5% reduction in their initial body weight. This technique may seem promising, but few studies provided adequate information regarding treatment fidelity. Half of the reviewed studies showed no statistically significant weight loss compared to the control group (Barns et al., 2015).

A more recent systematic review and meta-analysis of MI use in behavioral weight management programs included 46 studies (n= 11,077). MI was more effective at weight management than no/minimal interventions at six months, however, it was not statistically significant. Few studies included data at 1-year and 18-month follow-ups, which are important to understanding long-term weight loss maintenance (Michalopoulou, 2022).

Hardcastle et al. (2013) also aimed to assess the effectiveness of a low-intensity MI intervention in reducing cardiovascular disease (CVD) risk factors in a UK primary-care setting. The recruitment intervention group (n= 203) received 5 MI sessions in six months with a physical activity specialist and dietitian in addition to standard exercise and nutrition information. The control group only received the standard information from the clinician (n= 131). The results showed that the MI intervention led to long-term improvements in some health-related outcomes associated with CVD risks, such as walking and cholesterol levels, especially for patients with elevated CVD risk factors at baseline. However, the blood pressure, weight, and BMI improvements were not maintained after 12 months post-intervention (Hardcastle, 2013). The study suggests that MI interventions have potential in primary care settings, however, it does not indicate long-term weight loss success.

MI has shown mixed results with a slight potential for managing overweight and obesity by enhancing intrinsic motivation and behavior change. The mixed results of the effectiveness of MI techniques could be attributed to the inconsistency of the treatments delivered and the control group interventions. Common barriers to MI implementation include staff training and the increased use of physician time. MI provides an element of behavioral interventions that could be effective, but ultimately other behavioral change techniques should be used in addition to this technique.

Self-Monitoring for Behavior Change

Self-monitoring is a centerpiece of most behavior weight loss intervention programs. Self-monitoring involves tracking one's dietary intake, physical activity, and weight to increase awareness of their current behaviors (Burke et al., 2011). This method provides regular feedback about whether target behaviors are improving, degrading, or being maintained (Butryn et al., 2012). Self-monitoring in behavior change has a strong theoretical foundation from the self-regulation theory and is strongly associated with weight loss success. The self-regulation theory suggests that individuals must have strong self-regulatory skills to change habits successfully. This involves a process where individuals first self-monitor their behavior, followed by self-evaluation of the progress toward their goal. Cognitive activities (goal-setting, self-monitoring) improve the enactment of health behaviors (Bandura et al., 1997). With a clear assessment of progress provided by self-monitoring, individuals are also encouraged in behavioral interventions to set objective goals that can be easily measured. Goal setting is also an important behavior change technique that has shown effectiveness in literature reviews (Coupe et al., 2019).

Self-monitoring has been widely studied in behavior change and weight-loss research. The analysis of 22 studies that focused on self-monitoring behavior change for weight loss, specifically monitoring dietary intake, exercise, and self-weighing through paper diaries, revealed important insights about this intervention. A significant association between self-monitoring and weight loss was consistently found (Burke et al., 2011). While these results were subjected to some limitations, including the lack of validation of self-report measures, randomized controlled studies help provide further evidence on how this method is used in clinical research. In a randomized study of 52 subjects in a 16-week weight loss intervention, participants were provided a diary where they were prescribed caloric limits and physical activity goals. The paper found that weight loss was significantly associated with several self-monitoring diaries completed. The results indicate that self-monitoring is crucial in promoting weight loss and inducing changes in eating and physical activity behaviors rather than the specific details of what is being monitored (Helsel et al., 2007). Another study explored the traits linked to regular self-weighing and its correlation with sustaining weight loss in members of the National Weight Control Registry (n= 3003) who had lost 30 lbs or more and kept it off for over a year. This study found that consistent self-weighing helped individuals maintain their successful weight loss by allowing them to catch weight gains before they escalate and make behavior changes to prevent additional weight gain (Burtyn et al., 2007).

Self-monitoring is an effective and necessary component of behavioral interventions. It allows individuals to track their progress, gain self-awareness, and make informed decisions about their behaviors. Self-monitoring can also provide individuals with a clear assessment of their progress which could be used to set objective goals which minimize the intention-behavior gap.

Group Therapy

Group therapy is another tool that research has targeted to establish intermediate and long-term outcomes of personalized therapy. The group setting also allows individuals to share their experiences and struggles with others who are going through similar challenges and to receive feedback and encouragement from their peers. This can reinforce positive behaviors and motivate them to continue with the weight loss process. Burtyn et al. (2011) stated that group therapy addresses sociological and psychological elements of weight loss behaviors through a more cost-effective and scalable process.

Group therapy was used in both the DPP and the Look AHEAD studies. Typically, group therapy is guided by professionals with degrees in nutrition, psychology, or a related field, and each session lasts 60 to 90 minutes in groups of 10 to 15 participants (Wadden et al., 2000). To examine the effectiveness of group-based interventions, a systematic review of 5 trials (n=336) found that group-based weight loss treatments were more effective than individual-based treatments after 12 months. The review stated that group-based weight-loss interventions might be more effective than individual-based interventions when considering the need for widespread implementation of behavioral interventions to address the growing obesity pandemic (Paul-Ebhohimhen, 2009). There are limited research studies that only use group therapy compared to individual therapy; most comprehensive behavioral interventions use both methods. One landmark randomized controlled trial compared group therapy interventions to individual therapy interventions. In 75 obese adults, group therapy led to greater weight reductions than individual therapy at the end of their treatment, and treatment conditions showed equivalent improvements in psychological functioning (Renjilian et al., 2001). A more recent group therapy intervention paper found similar success surrounding its success at addressing mental health. The study was conducted with 67 obese adults who went through 22 sessions of cognitive behavioral group therapy over a year. Participants in the study reported increased self-esteem, physical activity, and satisfaction with their body weight (Dalle Grave et al., 2020).

While group therapy offers a more cost-effective option, it faces challenges with the reproducibility and replicability of its intervention in clinical trials. While individual therapies provide a space where individuals can share sensitive information with trained professionals, group therapy allows individuals to share their experiences, receive feedback, and get encouragement from peers facing similar challenges. This narrative review suggests that both methods should be utilized to tackle behavioral weight loss interventions.

Chapter 1 Discussion

Overweight and obese populations pose a growing burden that has led to a costly pandemic in both developing and developed nations. As the prevalence continues to rise in the United States and worldwide, obesity affected 42.4% of US adults in the 2017-2020 time period, and is projected to increase to 48.9% by 2030. This tremendous burden of disease has been estimated to cause 3.4 million deaths, 3.9% of years of life lost, and 3.8% of disability-adjusted life-years worldwide. This issue is considered a global pandemic by the WHO which has widespread effects on health and the global economy. Individuals who are obese and overweight experience a higher all-cause mortality rate, increased psychological and sociological detriments, hundreds of billions of dollars in additional healthcare spending, and pose a greater environmental impact compared to normal weight populations. This multifaceted problem has led to a wide array of weight-loss management techniques which include nutrition and physical activity modification, pharmacotherapy interventions, bariatric surgery, and behavioral interventions. While moderate success has been shown in all weight management techniques, a comprehensive behavioral intervention is a critical component to maintaining weight loss according to the AHA, ACC, NIH, CDC, and WHO. These interventions target creating new health behaviors which contribute to a long-term gradual weight loss, which should minimize the rebound effect. Successful behavioral interventions for weight loss include CBT, MI, self-monitoring, and group therapy. These methods are designed to restructure cognitive schema by addressing the underlying causes of the original weight gain, and hopefully increase self-efficacy and self-regulation to prevent weight regain, leading to sustained weight loss and improvements in overall health outcomes. However, these interventions are often time-intensive and require trained health professionals which can be costly and unscalable to address the obesity pandemic that is increasing at an alarming rate. As doctors and healthcare workers become increasingly overburdened with the worsening shortage, innovation has provided a new method of providing behavioral interventions that can be scaled to address the pandemic. Mobile health (mHealth) weight loss behavioral interventions have emerged as a promising solution, as they allow individuals to receive treatment and support through mobile devices. This delivery mode reduces the need for in-person appointments and enables remote monitoring and personalized coaching. Furthermore, mHealth interventions have shown to be effective in promoting weight loss, improving dietary habits, increasing physical activity, and enhancing self-management skills, all of which are critical components for long-term weight management success. As the prevalence of obesity continues to rise, mHealth interventions could play a critical role in addressing this growing burden by providing accessible and effective behavioral interventions that can be scaled to reach large populations in need. The next chapter will address the rise in mHealth interventions for weight loss management in overweight and obese populations, as well as a content analysis and quality assessment of the leading mHealth interventions on the public market.

Chapter 2 : mHealth Weight Loss Management Techniques

Introduction

Chapter 2 Synopsis

Since the inception of the smartphone, the speed, accessibility, and direct communication enabled a boom of innovation to use this new tool to solve our most pressing health concerns at a population level. mHealth interventions are an emerging field that leverages the capabilities of smartphones to improve health outcomes and delivery of healthcare services. These interventions are more cost-effective and scalable to address the worsening obesity pandemic. As app developers quickly produce new mHealth apps, which total over 350,000 different apps today, scientific research surrounding the efficacy has been slow to catch up and determine if mHealth-delivered interventions are effective, and if they are, which features provide the most benefit for changing behavior and producing better health outcomes (Byambasuren et al., 2019). This chapter will first overview the technological advancements that led to the emerging eHealth and mHealth intervention fields. Next, a literature review of systematic reviews of eHealth and mHealth interventions identified moderate weight loss success, reductions in BMI, improvements in nutritional patterns, and increased physical activity. In order to imitate successful in-person behavioral interventions, mHealth app features must provide features to increase app adherence and user engagement. A review of evidence based strategies in mHealth weight loss interventions overviews the importance of including behavior change techniques, which can be made "fun" through gamification strategies and reinforced by ecological momentary interactions and assessments. To provide the social support that has been proven effective in group therapy, online social networks could potentially attempt to fill this needed gap in the solitary nature of mHealth interventions. Finally, the chapter will review the literature surrounding the quality assessment and content analysis of popular physical activity apps, nutrition-based apps, and general weight loss apps. While most apps reviewed showed limited behavioral change techniques, gamification, and social support, the literature provides evidence of clear frontrunners, including Noom.

Rise of Smartphone Technologies

In the last 20 years, there has been a significant shift in the rise of mobile technologies, which has led to a dramatic transformation in how people communicate and access information. IBM developed the first smartphone in 1993, which featured a touchscreen, email capacity, and several built-in apps. The first smartphone fell flat, weighed a pound, cost $899 in 1994, had a one-hour battery life, and after six months of sales and 50,000 units sold, the product was taken off the market (Aamoth, 2014). This failure was followed by a decade of innovation which led to the introduction of color screens in 2001, 3G networks that provided faster internet connectivity in the early 2000s, the colored touchscreen from the original iPhone in 2007, along with cameras, app stores, and major innovations within the operating systems hardware (New York Times, 2013). In 2021, Pew Research Center found that a vast majority of Americans, 97%, own a mobile cellphone, 85% of whom own a smartphone. In 10 years, smartphone ownership in the United States has gone from 35% in 2011 to 85% in 2021. Due to the lack of traditional home broadband services, 15% of American adults depend on their smartphones to access the internet (Pew Research Center, 2023). Not only have smartphone technologies led to a transformation in communication and internet access, but they have led to a restructuring in our daily time management. While statistics vary by age, gender, and other demographic factors, the average time spent on a smartphone in the US is 3-5 hours daily (Jefferson, 2022). Mobile technology has also spread rapidly around the globe. Some estimate that there are over 6-6.5 billion smartphone users worldwide (Rosenberg, 2020). The surge in computing power and mobile connectivity has fashioned a global boom in smartphone usage. The boom in smartphone innovation has increased mobile health applications.

The speed, accessibility, and direct communication of mobile technologies have enabled the sharing of health information. The rapid development of new mobile health technologies falls under the term mHealth or mobile health. mHealth is defined by the WHO as "medical and public health practices supported by mobile devices, such as mobile phones, patient monitoring devices, personal digital assistants, and other wireless devices" (WHO, 2011). The use of mHealth is on the rise, serving multiple purposes such as (1) communicating with patients, monitoring their progress, and providing education, (2) easing the burden of disease linked to poverty, (3) enhancing access to health services, aiding clinical diagnosis and promoting treatment adherence, and (4) managing chronic diseases (Marcolino et al., 2018). mHealth methods of improving the quality of care can be adapted on a large scale at a low cost. Evidence regarding the effectiveness and cost-effectiveness of mHealth interventions is constantly growing, but the efficacy of these interventions is mixed.

Marcolino et al. (2018) conducted a systematic review of 23 systematic reviews involving 371 studies and over 79,655 patients to evaluate the diverse use of mHealth interventions. Methods used included text messaging or a reminder/alert for health education, behavior motivation, and prevention measures. The paper found that while evidence for efficacy is still limited, mHealth interventions have had a beneficial impact on health conditions such as asthma and chronic disease management. mHealth interventions have been attributed to increased appointment attendance rates and smoking abstinence rates. The landmark study highlights the magnitude of applications in which mHealth has been studied when treating various diseases.

With over 350,000 different mHealth apps available in the app stores, finding the right mHealth app is challenging for doctors and patients (Byambasuren et al., 2019). Based on the PWC Provider Survey, in the U.S., 56% of physicians have discussed mHealth with patients, and 26% have been asked about mHealth by a patient (Rowland et al., 2020). Despite the growing interest from patients and healthcare providers, there needs to be more clinical guidance on which mHealth apps should be utilized to add value to patient care. The following chapter highlights landmark studies in the efficacy of mHealth interventions, which specific features are necessary to create healthy weight loss behavior change, and a literature review of the quality and content analysis of the most popular mobile health apps on the app stores.

Literature Review of Reviews for eHealth and mHealth Interventions Related to Weight Loss

In comparing the use of technology in weight-loss interventions, it is important to differentiate between mHealth and Electronic Health (eHealth) technologies. mHealth and eHealth technologies differ in their use for healthcare delivery. mHealth uses mobile devices for health-related purposes, while eHealth uses electronic communication and information technology tools to support health services delivery and promote health. While mHealth technologies focus their interventions on the patient level, eHealth technologies often have a broader scope, encompassing the entire healthcare system. This literature review is focused on individual behavior change, therefore most of the studies provided are mHealth interventions, with one study focusing on eHealth due to its high impact on the literature in this field.

To identify relevant studies investigating the effectiveness of mHealth and eHealth interventions in promoting healthy behaviors for weight loss, a comprehensive narrative review was performed in three prominent databases, including Google Scholar, Web of Science, and PubMed. To be included, studies were required to have implemented mHealth or eHealth technologies as an intervention to improve dietary habits, physical activity, and weight loss prevention behaviors. Common limitations of these reviews included small sample sizes, short follow-up periods, varied content and theoretical basis of interventions, and modes of treatment delivery.

Hutchesson et al. (2015) published a landmark paper which provided a background and historical review on the use of eHealth interventions in the treatment of overweight and obesity in adults. The systematic review and meta-analysis included interventions that used eHealth tools through the internet, email, text messages, monitoring devices, and mobile applications from 1995 to 2014. This systematic review examined 84 studies to determine the efficacy of eHealth interventions compared to traditional methods of intervention delivery, and compared the efficacy of various eHealth interventions for weight loss, weight maintenance, and weight gain prevention. In the meta-analysis, stand-alone eHealth interventions resulted in a modest weight loss of -1.4 to -2.7 kg post-intervention, compared to receiving little or no treatment. eHealth interventions that included additional in-person components led to significantly greater weight loss. Hutchesson et al. (2015) also found that eHealth weight loss interventions with evidence-based behavior features (e.g., self-monitoring, personalized feedback) also achieved significantly greater weight loss (Hutchesson et al., 2015). Further studies on mHealth interventions have shown to support these findings.

Schoeppe et al. (2016) analyzed studies from 2006 to 2016 using a smartphone mHealth app to improve diet, physical activity, or sedentary behavior. In the 27 studies included, most were randomized controlled trials targeting adults, and the outcomes measured were changes in health behaviors and weight-related biomarkers. The paper indicated modest evidence in stand-alone mHealth interventions and found that multi-component interventions are overall more effective. Some consistent mHealth app features identified in most interventions were goal-setting, self-monitoring, and performance feedback. These features were found to increase weight loss, according to Hutchesson et al. (2015). Schoeppe et al. (2016) indicate that future research needs to determine which app features and behavior-change techniques increase user engagement and intervention efficacy (Schoeppe et al., 2016).

Another systematic review and meta-analysis provided a narrower scope of papers surrounding mHealth mobile phone apps to promote weight loss and physical activity. Twelve articles from 2010-2015 were included because they compared mobile phone app interventions to a control group intervention. The resulting meta-analysis indicated a significant reduction in body weight (1.04 kg), BMI (0.43 kg/m^2), and non-significantly increased physical activity. The modest weight loss reported could be attributed to the control group interventions often involving an activity outside of the usual care. The study did not indicate common app features or behavior change techniques used. However, it did mention how the portability of a mobile phone intervention allows users to access health-related apps and has the potential to facilitate long-term management and reinforcement of healthy behaviors (Mateo et al., 2015). Mobile phone portability offers the potential for reinforcing healthy behaviors, and future research exploring effective app features and consistent interventions with behavior change theories could improve mHealth efficacy.

A recently published literature review provided a systematic review of systematic reviews, including various mHealth interventions that focused on increasing self-monitoring habits to manage participants' obesity and diabetes. The 17 reviews from 2005 through 2019 were analyzed, and six reviews were used in the meta-analysis. A meta-analysis of three reviews, which measured the effect on HbA1c values, revealed that mobile app mHealth interventions alone resulted in a statistically significant reduction of .25% to 0.48% decrease. The effects of the mHealth interventions on BMI were varied, with five reviews reporting large improvements and three reporting small or no effect. The meta-analysis of six reviews reported body weight losses of -1.04 kg to -2.35 kg and a decline in BMI of -0.43 kg/m2 to -0.77 kg/m2. The results concluded that mHealth was feasible and could potentially improve health outcomes among patients with diabetes or obesity (Wang et al., 2020).

According to the research conducted by Hutchesson et al. (2015) and Schoeppe et al. (2016), multi-component mHealth interventions demonstrated greater effectiveness in comparison to stand-alone mHealth interventions. To test this finding, Anton et al. (2022) identified 35 studies investigating the efficacy of mHealth mobile apps for weight loss and completed a meta-analysis to determine if stand-alone mHealth interventions were comparable to mHealth interventions that included an additional human behavioral coaching component. Stand-alone mobile phone mHealth interventions resulted in a weight loss of -1.99 kg and -2.80 kg at 3 and 6 months. Incorporating a human behavioral coach alongside a mobile app mHealth intervention resulted in statistically significant weight loss of -2.09 kg and -3.77 kg at 3 and 6 months, respectively. While this finding limits the intervention's scalability, recent advancements in artificial intelligence could replace this human-delivered component (Antoun et al., 2022). A review of the app features found that most included self-monitoring, personalized feedback, education, social support, rewards, and gamification, with most apps incorporating only one to two of these features.

This literature review of systematic reviews and meta-analyses offers insights into the efficacy of eHealth and mHealth interventions in promoting weight loss and behavior change. Stand-alone eHealth interventions effectively achieve a modest weight loss of -1.4 to -2.8 kg, but those with in-person support led to a greater weight loss. Stand-alone mHealth interventions also show modest BMI reductions of -0.43 kg/m2 to -0.77 kg/m2. mHealth interventions with in-person support lead to statistically significant weight loss. While eHealth and mHealth interventions are scalable and cost-effective, so far they appear to remain somewhat less effective than approaches that also incorporate traditional in-person interventions. Some key features that have been identified to improve user engagement and adherence in the intervention include the incorporation of gamification and behavior change techniques such as self-monitoring, goal-setting, social support, personalized feedback, educational tools, and rewards. Overall, this literature research suggests that mHealth interventions do not provide adequate features to influence behavior change.

While app features vary, the goals of mHealth interventions should reflect in-person behavioral interventions. Successful in-person behavioral interventions for weight loss are comprehensive and time-consuming, therefore mHealth interventions must provide features to increase app adherence and user engagement. The following section highlights key features that could lead to better user engagement and adherence in mHealth weight-loss programs.

Evidence-Based Strategies in mHealth Weight Loss Interventions

As discussed in chapter 1, in-person behavioral weight loss techniques address the multifaceted nature of overweight and obese populations. While the cognitive psychology theories of behavior change differ, the interventions attempt to reach a common goal: to motivate individuals to replace their detrimental behaviors that led to the original weight gain with healthier habits and practices. The literature has identified several features that have been shown to lead to successful weight loss behavioral interventions. They should be tailored to target the underlying social and psychological determinants impacting an individual's actions and to reshape these cognitive frameworks into new, healthier habits. They also use goal-setting, which are measurable goals that can be tracked through frequent self-monitoring to increase self-awareness of food intake, physical activity, and weight loss progress. In addition, the interventions must include comprehensive education on nutrition, specifically addressing healthy eating habits, portion control, and balanced diets. Behavioral interventions must also increase physical activity by creating new habits in their daily life and tailoring the activity to the individuals' preferences and fitness levels. Finally, group therapy is important in enabling individuals to exchange experiences, obtain feedback, and gain social support from peers confronting similar obstacles. These features must be reinforced with motivational enhancements to increase confidence and self-efficacy, ultimately empowering individuals to sustain their commitment to change.

As mHealth interventions emerge and flourish in the scientific literature, techniques to increase user engagement and intervention adherence have been studied extensively to improve the quality of the current mHealth technologies available to the general public. This narrative review will discuss the evidence behind several features, including behavior change techniques and gamification, through the incorporation of ecological momentary interventions and assessments, and social networks.

Behavior Change Techniques

For in-person behavioral interventions, classifying the theoretical models of behavior change used within the clinician-patient interaction can often be difficult. While clinicians can do their best to adhere to a theoretical model to influence a healthy behavior, in practice, there is no way to know which techniques are utilized. This is because behavior change is complex and influenced by many factors, including the individual's motivations, beliefs, and life circumstances. As a result, clinicians must be flexible and adapt their approach to meet the needs of each individual patient.

In mHealth interventions, behavior change techniques can be examined based on the features of the intervention. A behavior change technique (BCT) is defined as “an observable, replicable and irreducible component of an intervention designed to alter or redirect causal processes that regulate behavior” (Michie et al., 2013). Essentially, a BCT is the smallest “active ingredient” of an intervention which includes goal-setting, self-monitoring, knowledge, action planning, social support, and feedback. These techniques have been clearly defined and linked to theories of behavior change which comprises 93 individual techniques, grouped into 16 behavior change categories. While this taxonomy is more detailed, Abraham et al. (2008) developed a 26-category taxonomy that is broader and provides a general overview of the types of techniques instead of the individual techniques. Both taxonomies have been widely used in the quality assessment and content analysis of mHealth smartphone applications.

The effectiveness in the number of BCTs within a mHealth intervention has been studied extensively. A systematic review and meta-analysis included 85 mHealth studies (n=43,236); these studies were randomized, used BCTs in their interventions, and measured a behavior change. The review found that incorporation of more BCTs had a larger effect on behavior than interventions with fewer techniques. In addition, outcomes were enhanced by additional forms of communication specifically through text messages (Webb et al., 2010). The evidence of which BCTs lead to better outcomes was inconsistent. However, some interventions using the BCTs that are congruent with Control Theory have been associated with increased intervention effects. Control Theory suggests that behavior changes are achieved through actions to meet the individual goals that are set (Carver et al., 1982). Some BCTs congruent with the Control Theory are self-monitoring, goal setting, providing feedback on performance, and a review of behavioral goals (Samdal et al., 2017). A meta-analysis of 122 studies for interventions designed to increase physical activity and healthy eating found that “self-monitoring” explained the greatest amount of among-study heterogeneity. The study found that combining self-monitoring with at least one other technique derived from the Control Theory was significantly more effective than other interventions (Michie et al., 2009). Dombrowski et al. (2012) studied BCTs in behavioral mHealth interventions in obese adults and found similar findings regarding the effectiveness of

BCTs linked to the Control Theory. A further review of 48 studies of interventions using BCTs for physical activity and overweight obese adults found that self-monitoring and goal setting is suggested when counseling overweight and obese adults (Samdal et al., 2017). While studies have found clear frontrunners in which BCTs should be targeted in interventions for overweight and obese individuals, it is still recommended to use more BCTs within the mHealth intervention to increase effectiveness and user engagement. With over 93 individual behavior change techniques, this can be overwhelming to a mHealth user. The next section discusses gamification which has been shown to be an effective way to integrate the BCTs in a format that further enhances user engagement.

Gamification

Gamification uses game elements and design in non-game contexts to encourage engagement and motivate behavior change. They can be rewards, prizes, avatars, badges, leaderboards, competitions, leveling-up or health-related challenges (Edwards et al., 2016). Gamification integrates behavior change techniques through leveraging the desire for competition which can engage and motivate users. An ideal gamification technique isolates the features that make games addictive and add those features to mHealth interventions to make them addictive, too (Cugelman, 2013). A landmark review of successful gamification techniques categorized the techniques into seven persuasive strategies: goal setting, capacity to overcome challenges, providing feedback on performance, reinforcement, comparing progress, social connectivity, and fun and playfulness. These persuasive strategies are typically implemented by providing clear goals, using levels, showing progress, giving rewards, providing badges for achievements, showing game leaders, and giving a story or theme (Cugelman, 2013).

Gamification in mHealth apps to alter health behaviors has been used in targeting physical activity, healthy eating, and weight loss. A review of 19 studies found that gamification has been demonstrated to positively impact emotions, behavior, cognition, and user experience. A majority (59%) of the studies reported gamification to influence the health and well-being of the user positively, and no direct negative impacts were reported. A significant portion (41%) of studies reported mixed or neutral effects. While results showed modest increases in health-related behaviors, there was mixed evidence for cognitive outcomes (Johnson et al., 2016). Similar findings were found in different literature reviews and meta-analyses (DeSmet et al., 2014; Hamari et al., 2014).

The widespread use of gamification has also been studied in weight loss research. A review of 14 papers from 2005-2013 was examined to determine if health video games were combating childhood obesity. The study found that 40% had positive outcomes related to obesity, while the other studies found neutral results (Lu et al., 2013). These results were also reflected in a systematic review and meta-analysis of 16 randomized controlled trials on gamification in physical activity interventions. The study found that the effect was statistically significant when gamified interventions were compared with inactive control groups, with no moderators such as age, gender, and BMI (Mazeas et al., 2022).

Gamification has been shown to improve user experience and provide a fun way to address behavior change techniques like goal setting, self-monitor progress, providing educational tools, and many others. mHealth interventions should incorporate this tool to engage individuals in the app to increase adherence and motivation for behavior change. Further research is needed to understand the relationship between gamification and health behavior change.

Ecological Momentary Interactions and Assessments

As previously discussed, BCTs related to the Control Theory (e.g., goal setting, self-monitoring, and providing feedback on performance) have been associated with increased intervention effectiveness (Dombrowski et al., 2012; Michie et al., 2009; Sandal et al., 2017). Self-monitoring provides individuals with objective feedback on their progress toward their goals, thus allowing them to adjust their behavior to stay on track. This, in turn, can reduce the intention-behavior gap, which is the gap between a patient's intent to do behaviors but does not follow through (Faries et al., 2016). As previously mentioned, gamification techniques can use game elements to incorporate BCTs like goal setting and self-monitoring. However, incorporating these gamification elements can be challenging. This is where ecological momentary interactions and ecological momentary assessments come into play.

Ecological momentary interactions (EMIs) are treatments provided to people during their everyday lives in their natural settings (Smyth et al., 2011). EMIs differ from ecological momentary assessments (EMAs). EMA is a data collection method that captures respondents' emotions, activities, or behaviors in their natural element (McDevitt-Murphy et al., 2018). In short, EMIs deliver ‘homework’ and instructions to engage in specific behavior, while EMAs deliver prompts to self-reflect and describe their natural state. For decades, therapists have been urging patients in psychotherapy to engage in tasks, practice their skills, and fulfill tasks outside of therapy sessions. Recently, psychosocial health behavior treatments outside the clinical setting have utilized these mHealth techniques with individuals as they live their daily lives.

EMAs and EMIs delivered by mHealth methods have been studied extensively and are an emerging field of mHealth-delivered psychotherapy interventions due to their scalability, treatment efficiency, and reduced intervention cost. The success of EMA and EMI components has led to the adoption of fields outside of psychotherapy like smoking cessation, weight loss, anxiety, diabetes management, eating disorders, alcohol use, healthy eating, and physical activity (Smyth et al., 2010). A landmark literature review also found that EMIs delivered by mobile phones are successful, accepted by patients, and effective for improving various health behaviors (Smyth et al., 2010). Smyth et al. (2010) also stressed the importance of individualizing EMIs sensitive to their ecology. A decade later, Dao et al. (2021) included a review of 19 studies that reflected these results by providing evidence that the users perceived EMIs to be helpful and suggested increased personalization, multimedia, and interactive capabilities to increase user compliance. The generalizability of the studies is difficult because EMI and EMA components are rarely reported, particularly due to no standardized methods (Dao et al., 2021).

Limitations of literature reviews of EMI and EMA interventions generate a large variety of data (e.g., dietary, behavioral, physical, sociopsychological) which presents difficulties in examining concurrent exposures and events. The mobile delivery of the EMIs and EMAs is an emerging area of research; studies often have small sample sizes and are difficult to generalize due to no standardized intervention components and a lack of efficacy evaluation. When assessing mHealth-delivered EMI/EMA interventions, it is essential to take into account the specific terminology used in the papers. For example, an EMI could be a text message or a reminder notification, and an EMA could be described as a self-monitoring intervention. By bridging this gap in literature terminology, the studies surrounding the efficacy of mHealth-delivered EMI/EMA (but using different terminology) interventions provide evidence that this practice is a critical component of weight-loss programs.

A text message is an EMI intervention often used in weight management studies. A systematic review of eight studies highlighted the effectiveness of these interventions in overweight adolescents. Of the eight studies, seven demonstrated a reduction in BMI which averaged 1.3% to 4.5% after 6 months (Partridge et al., 2020). The literature suggests that a text message intervention could be part of an effective mHealth weight-loss intervention. Another randomized controlled trial measured the text-message stand-alone intervention in 65 overweight/obese adults. After 4 months, the intervention group (n=33) lost 1.97 kg more than the control group (Patrick et al., 2009). The two studies highlight the delivery of EMIs through text messages as an effective tool in mHealth weight loss interventions.

As mentioned in chapter 1, self-monitoring is a fundamental element for in-person behavioral weight loss interventions (Burke et al., 2011). Self-monitoring involves the practice of documenting an individual's dietary intake and physical activity, enabling them to gain insight into their current behaviors (Burke et al., 2011). This definition is nearly indistinguishable from the definition of an EMA. A systematic review of 22 studies identified a significant positive relationship between self-monitoring practices (primarily using a paper diary) of diet, physical activity, or weight and successful outcomes related to weight management (Burke et al., 2011). Burke et al. (2012) then used the current advancements in mobile technology to discover if self-monitoring could be as effective in a mHealth intervention. To determine if a paper diary or an electronic self-monitoring delivery was more effective, a randomized controlled trial studied 210 overweight/obese adults over two years. With a retention rate of 85%, the electronic self-monitoring intervention with tailored feedback (PDA+FB) was superior to using a paper diary for weight loss. While the PDA+FB use resulted in a small weight loss, the study also found greater adherence to self-monitoring when delivered by a mHealth technology compared to traditional methods (Burke et al., 2012).

These findings were supported by Hutchesson et al. (2016) that adding extra individualized feedback and reminders can enhance self-monitoring in a mHealth weight loss program. The randomized sample of 301 overweight/obese adults found that incorporating individualized feedback and reminders into a commercial web-based weight loss program resulted in greater adherence to self-monitoring of food, exercise, and weight loss during a 12-week period compared to the control. This highlights the potential of individualized EMI/EMAs to facilitate greater adherence to self-monitoring, which has been shown to ultimately lead to greater success in weight loss programs (Hutchesson et al., 2016).

As aforementioned, EMI/EMA techniques are already being used under different literature terms. The absence of established guidelines for analyzing the techniques utilized by mHealth interventions has resulted in a variety of terminology used within the literature. EMI/EMA's should be a key feature in all mHealth weight loss interventions because they provide improved user engagement, deliver self-monitoring interventions more effectively than traditional methods, and show modest stand-alone success for weight loss and healthy behavior change. As the mHealth behavior interventions adapt to the increasing volume of research, mHealth feature terminology needs to be standardized to facilitate clear communication and consistency across studies and improve the reliability and validity of findings.

Online Social Support

Most mHealth interventions are delivered remotely and are solitary in nature, yet as discussed in chapter 1, social support has been shown to be an important factor in weight loss interventions. Social support networks are important for long-term weight-loss success (Wang et al., 2014). Social support for behavior change is based on an evidence based-theory called the social cognitive theory, which proposes that behavior is influenced by a complex interaction between personal, behavioral, environmental factors, and the observation of other behaviors (Bandura, 2003). In essence, supportive friends or family members can help provide emotional support when an individual is discouraged and can help provide feedback of healthy eating and exercise goals.

As the use of social media for health promotion is a developing area of study, early research suggests that it enhances participant involvement and may offer a cost-efficient method for delivering social support to individuals participating in weight loss programs (Jane et al., 2018). A review of the evidence found that there are mixed results for social media engagement and weight loss success. An example of a study that supports this finding ran a sub-analysis of study participants (n=47) to examine if online social networking on Twitter can help enhance weight loss. At 6 months, reported weight loss predicted engagement with Twitter, but this engagement was only related to minimal weight loss. The participants typically used the platform to provide informational support through status updates (Turner-McGrievy et al., 2013).

Another 6-month, minimal contact intervention studied 96 obese adults who were randomly assigned to a podcast only or podcast+ mobile app group. Both groups received 2 podcasts a week, and the mobile app group was instructed to use a monitoring app and to interact with study counselors and other participants on Twitter. Both interventions were minimally intensive which resulted in a minimal weight loss (-2.7%). The podcast, app and Twitter intervention did not statistically enhance weight loss at 6 months compared to the control group (Turner-McGrievy et al., 2013).

A similar finding from a 6 month physical activity intervention that utilized social networks in 55 participants found a non-statistically significant increase in average daily step count between baseline and 6 months. A further subgroup analysis comparing higher and lower physical activity groups at baseline showed the latter had a statistically significant increase in their daily step count (Tong et al., 2019). A systematic review and meta-analysis of 14 studies that used social features in mHealth physical activity interventions found non-significant effects on physical activity outcomes. The preference of social features were mixed, some felt more motivated by social support and competition, while others voiced concerns about comparison (Tong et al., 2018).

In the emerging field of the use of social networks in mHealth interventions, there is mixed evidence surrounding the efficacy of this tool to increase social support within the solitary nature of a mHealth intervention. Ultimately, it depends on the user's preferences, whether they view the posts as social support or make them feel discouraged through comparison. Since the COVID-19 pandemic, there has been widespread adoption of online group therapy, which is another online social network intervention that has been subject to scientific investigation. A landmark systematic review and meta-analysis (n=64) found that internet group therapies provide a legitimate therapeutic effect. In 14 studies that examined the difference between face-to-face and internet interventions, there were no differences in effectiveness (Barak et al., 2007). While there are limitations in online group therapy, further investigation should determine if this is an effective tool to integrate into mHealth weight loss interventions.

Overall, enhancing social networks through online methods may never substitute the effectiveness of a social support from a trusted friend or family member. It is suggested that mHealth apps attempt to provide social networking opportunities or online group therapy. However, education on how to reach out and engage a friend or family member to support the individual in their weight loss journey may be an effective way to supplement the critical component of social support that is needed in the weight loss journey.

Content Analysis of Popular Weight-loss Smartphone apps

App development has followed the recent boom in mobile technology, which has led to over 350,000 different mHealth apps available in the app stores. Therefore, finding the right mHealth app is often challenging for doctors to navigate the extensive market to make recommendations for patients (Byambasuren et al., 2019). With a growing interest from patients and healthcare providers surrounding which mHealth apps are most effective, quality reviews and content analysis of the most popular apps on the Apple and Google stores has provided some recommendations. The following review of literature highlights the reviews surrounding popular physical activity promotion apps, nutrition and diet apps, as well as general weight-loss applications. In general, most apps reviewed provided minimal BCTs, however, most included goal setting, self-monitoring, educational tools, and feedback on performance. Another commonality between the studies found that the apps need to increase scientific coverage and accuracy, and provide more gamification techniques. Social networks were generally an uncommon feature studied and measured. Finally, use of EMIs and EMAs were not mentioned under those names among the studies. Medication adherence reminders, which is a critical part to minimize weight-related comorbidities, were never mentioned in the studies either. The studies examined in this narrative review provided several mHealth app recommendations which included: Noom, Loseit!, MyFitnessPal, and My Diet Coach Pro.

Physical Activity Apps

Physical activity promotion is recommended as a significant component of weight loss interventions for individuals who are overweight or obese. A rise in mHealth mobile apps to increase physical activity has led to quality reviews of the current apps on the market. A review was conducted in 2013 to analyze the content and quality of the top-ranked apps (n=167) that were promoting physical activity, which included apps in both paid and free sections. Specifically, the review measured the number of behavior change techniques utilized in the physical activity smartphone apps. A latent class model consisting of two classes was developed to generalize the behavior change techniques employed. The first class (54% of apps) focused on physical activity motivation, with an emphasis on social and self-regulation of physical activity. The second latent class (46% of apps) focused on physical activity education. The review concluded that physical activity apps used a limited number of BCTs. The prevalent BCTs employed were educational in nature, focusing on providing information and demonstrations of specific physical activities, rather than emphasizing motivational factors to encourage action (Conroy et al., 2014). Another content analysis of BCTs used in popular physical activity apps found that in the 64 apps analyzed, on average 5 BCTs were used (range 2-8) out of the 23 BCTs. The most popular BCTs included self-monitoring, providing feedback on performance, and goal-setting. On the other side, motivational interviewing, stress management, relapse prevention, self-talk, role modeling, and prompted barrier identification were not found in any of the apps studied (Middelweerd et al., 2014). Bondaronek et al. (2018) conducted a recent review and content analysis of 65 popular physical activity apps to determine the use of BCTs. Each app contained at least one BCT, with an average number of 7, and a maximum of 13 BCTs of the 93 that were analyzed in the study. The most frequent BCTs used in the apps were self-monitoring, providing feedback on performance, and goal-setting (Bondaronek et al., 2018).

All three studies highlighted the limited number of behavior change techniques utilized in physical activity apps. The findings underscore the need for increased diversity in the use of BCTs in physical activity apps to enhance their efficacy in promoting behavior change and increasing user adherence.

Nutrition Based Apps

In addition to increasing weight loss through increased physical activity, chapter 1 also emphasized the importance of diet and nutrition notifications in weight loss intervention programs. Schumer et al. (2018) assessed the top 86 diet and nutrition apps in the Apple and Google Stores. The apps were evaluated by the BCTs included and identified the standard features used by the mobile apps. The study found that the most common features were dietary tracking and education, highlighting the inadequate use of BCTs (Schumer et al., 2018). A similar, more recent content analysis and quality assessment by Choi et al. (2021) studied 29 popular dietary apps in Korea, many of which are also available in the U.S. app stores. The apps were assessed by the content and quality through the number of BCTs used and the Mobile App

Rating Scale (MARS), which assesses the quality of mobile apps based on engagement, functionality, aesthetics, and information quality. The study found that most apps had tracking and motivational features, but few had rewards or follow-up management. Apps with more motivation and educational features may enhance the engagement of the app (Choi et al., 2021). Another quality review of 10 popular diet-tracking apps was studied based on their usability, using the System Usability Scale (SUS) and the behavior change domain features, which is different from BCTs. The presence of behavior change domain features was correlated with greater usability. While app features varied considerably, they all addressed some behavior change domain features and could have the potential to promote self-efficacy. There were also measurable differences between nutritional and dietary recommendations of the apps (Ferrara et al., 2019). Scozewka et al. (2022) examined the educational quality and dietary recommendations in popular diet and nutrition apps. A review of ten popular apps that provided customized meal plans showed that the nutrient requirements were similar across the apps. However, there were significant variations in the intake of different food groups (Soczewka et al., 2022).

Consistent findings of content analysis and quality reviews of popular nutrition and diet apps included standard features, including dietary tracking, educational tools, motivational tools, and an inadequate amount of BCTs. The quality review studies also found that there were inconsistent nutrition and dietary recommendations. Nutrition and dietary apps need to improve BCTs used to increase user motivation, self-efficacy, knowledge, and goal setting, which have been associated with increased app adherence (Bardus et al., 2016).

General Weight loss apps

Weight-loss apps often provide comprehensive programs encompassing physical activity, diet and nutrition, and weight tracking. Axar et al. (2013) provided a background to assess the quality of weight management apps to highlight the features consistent with behavior change theories. A total of 23 apps were chosen because they could track dietary behaviors and anthropometric measurements and did not require a subscription to any other program. The behavioral intervention strategies used in the apps were evaluated based on widespread behavior change theories using a 100-point behavioral theory score (BTS) scale that comprised 20 strategies. The apps were then ranked according to their BTS scores. The results found that all the apps included needed more theoretical content or guidance for behavior change. The maximum BTS score (out of 100) was 14, which went to LoseIt! The second highest was MyFitnessPal at 13 (Azar et al., 2013). The inefficient use of behavior change theories in popular weight loss apps is a common finding among most quality reviews.

Chen et al. (2015) provided a more recent quality assessment of the most popular smartphone apps for weight loss. Twenty-eight apps were included if they focused on weight management, self-monitoring to record dietary intake, and addressed dietary behaviors. Apps were evaluated based on the BCTs (26 points). Unlike Azar et al. (2013), this quality assessment also addressed scientific coverage and accuracy (32 points), usability (20 points), technology-enhanced features (14 points), and accountability (8 points). Of the 28 apps reviewed, the average scores are as follows: 6.3 out of 26 for BCTs, 18.8 out of 32 for scientific coverage and accuracy, 13.5 out of 20 for usability, 5.1 out of 15 for technology-enhancing features, and 3.5 out of 8 for accountability. Based on the scoring criteria, Noom scored the highest at 75 points, followed by Calorie Counter Pro at 65. Compared to Azar et al. (2013), MyFitnessPal scored 9th at 54.5 points, and Loseit! was not included in this paper. Common BCTs included self-monitoring, goal-setting, educational tools, and feedback on performance. This landmark quality review calls for the increased use of BCTs, scientific coverage and accuracy, and gamification to improve user engagement (Chen et al., 2015).

Bardus et al. (2016) also reviewed the 23 most popular apps that addressed weight control, diet, and physical activity. In addition to assessing the BCTs used (out of 33), the apps were assessed on their engagement, functionality, aesthetics, information quality, and content features. The study found that apps were of average quality and had consistently high functionality scores and consistently low information quality. Of the 33 BCTs reviewed, the apps averaged 10 techniques. The highest number of BCTs used was My Diet Coach PRO at 17. MyFitnessPal contained 11 BCTs, and Loseit! and Noom were not included in this paper. The most common BCTs were self-monitoring, goal setting, and personalized feedback. My Diet Coach PRO provided interactive coaching, a feature of Noom which was not examined in this paper. The takeaways of the paper include the need for more BCTs, increased information quality, and evidence-based content (Barbus et al., 2016).

Since the publication of these three landmark quality reviews and content analysis of popular weight loss apps, this narrative review failed to find recent reputable papers that examined the current weight loss apps on the market today. In the 7 years from the most recent publication, app quality may have improved due to the findings of the publication. Despite all reviewed papers having different behavior change scales, the studies indicated a general absence of BCTs/theories used. The papers highlighted the highest-ranked apps in behavior change methods: LoseIt!, MyFitnessPal, CalorieCounter, My Diet Coach Pro, and Noom. Self-monitoring, goal setting, personalized feedback, and educational tools were the most common behavior change methods. The reviewed studies also called for increased input from researchers and health professionals to guide the improvement and development of weight-loss apps with tailored and targeted nutrition advice, increased scientific coverage and accuracy, gamification, and other techniques to improve user engagement.

Chapter 2 Discussion

As the obesity pandemic worsens around the world tied with a national shortage of healthcare professionals to deliver effective behavioral interventions, technological interventions have met this modern problem with modern solutions. In the past 20 years, there has been a boom of smartphone adoption, with over 85% of Americans owning a smartphone today. This boom was met with a wave of innovative efforts to use the speed, accessibility, and direct communication to provide a cost-effective and scalable solution to the world's most pressing health problems. This gave way to the rise of mHealth interventions, which in its infancy, had shown to have positive benefits for asthma, smoking abstinence, chronic disease management, and weight loss management. Today, there are over 350,000 different mHealth apps available on the app stores. To assist clinicians and patients who are curious about which apps to use, the emerging scientific research has responded to provide evidence on the efficacy of mHealth and which features create an effective mHealth intervention (Byambasuren et al., 2019).

The literature review of systematic reviews included randomized controlled trials surrounding the effectiveness of various mHealth interventions to improve dietary habits, physical activity and other weight loss prevention behaviors. The landmark systematic reviews and meta-analyses indicated several similar findings. In summary, it was found that stand-alone mHealth interventions can achieve a modest weight loss averaging -1.4 kg to -2.80 kg, BMI reductions of -0.43 kg/m2 to -0.77 kg/m2, modest physical activity improvements, and significant declines in HbA1c. Evidence to date may suggest that comprehensive mHealth interventions are similarly effective as in-person behavioral interventions. Interventions with additional in-person coaching significantly increase weight loss success. With the new breakthroughs in AI-delivered behavioral coaching, further research is needed to determine if this feature could provide improved weight-loss success. The systematic reviews indicated that mHealth interventions should attempt to follow features of successful in-person interventions which are comprehensive, time-intensive, and target behaviors through theoretical behavior change models. Therefore, mHealth interventions should further develop gamification techniques and rewards to increase app adherence and user engagement, which was found to moderate the success of the intervention. Common features of effective mHealth interventions had included goal setting, self-monitoring, personalized feedback, and social comparison. However, many interventions employed only a few behavior change techniques.

To further understand which features produce effective mHealth interventions, a literature search provided insight into the evidence-based mHealth features that must be included. Some studies found that self-monitoring, goal setting, and other BCTs related to the Control Theory are associated with increased intervention effects. Additionally, a greater number of BCTs results in a larger behavioral impact, however, incorporating more BCTs should be done in a way that increases user experience. This is where gamification steps in. Through using the features that make games habit-forming, and using those features in a mHealth intervention, the goal is to also make the intervention habit-forming. The incorporation of gamification techniques to reinforce BCTs demonstrated positive impacts on emotions, behaviors, cognition, and user experience. EMIs and EMAs demonstrated profound stand-alone effects on behavioral interventions, which emphasized the importance of including text messages and self-monitoring which have shown to be key components in improving adherence and success in behavior change programs related to weight loss. Finally, to address the social support that is critical in the success of in-person interventions, online social networks demonstrated mixed results and often depended on the person. This narrative review suggests further research should include the use of online group therapy and educational programs on how to seek out and engage a friend or family member to provide social support throughout their weight loss journey. In all, the incorporation of these evidence-based mHealth features is highly recommended to improve the user experience and adherence in mHealth behavioral interventions for weight loss.

To determine if these methods are used within the current app market, a review of landmark quality reviews and content analysis of popular mHealth apps related to physical activity, nutrition, and general weight loss provided insight about the use of these practices. The literature surrounding the quality assessment of current mHealth apps tailored to physical activity, nutrition, diet, and general weight loss reveals essential insights into features and intervention components of popular mobile apps. The studies reviewed indicate a general absence of BCTs incorporated in the design of weight loss, physical activity promotion, and dietary and nutrition apps. The most common BCTs included behavior tracking, motivational features, educational features, and feedback. While this review did not highlight the effective behavioral features for weight loss interventions in smartphone apps, it did provide insight into the standard features used and the importance of user engagement through functionality, usability, and technology-enhanced features. The reviewed studies called for increased input from researchers and health professionals to guide the improvement and development of weight-loss apps with tailored and targeted nutrition advice, increased scientific coverage and accuracy, gamification, and other techniques to improve user engagement. While these studies reviewed standard features of the apps, they should have mentioned a critical feature that should be a part of any weight loss intervention.

As mentioned in chapter 1, individuals who are obese and overweight struggle with comorbidities like diabetes, hypertension, dyslipidemia, osteoarthritis, and sleep apnea. In order to control these persistent health detriments, people are frequently given various medications to alleviate the symptoms and avert additional harm to the body caused by these diseases. These medications should be taken at least 80% of the time to reach their optimal therapeutic effect. Unfortunately, for those using medication to manage their chronic illness, only 50% of drugs are taken as prescribed (Kini et al., 2018). Non-adherence poses a tremendous threat to the health and management of disease in overweight and obese populations. Medication management is critical in treating obese and overweight populations, yet quality reviews on physical activity, nutrition, and general weight loss mHealth apps fail to recognize this needed feature. Additional research into mHealth strategies for weight loss should consider whether a feature for reminding users about medication adherence is available. In all, Noom, Loseit!, MyFitnessPal, and My Diet Coach Pro were some of the highest-ranked apps based on this literature review. Loseit!, MyFitnessPal, and My Diet Coach Pro all have minimal scientific validation in the efficacy of their weight loss interventions, therefore, it is out of the scope of this narrative review to include these studies. Noom is widely recognized as a leader in mHealth interventions, having been the first fully mobile program to receive official recognition by the CDC as a diabetes prevention plan (Caffery, 2022). Therefore, Chapter 3 will provide a case study on Noom, specifically a literature review of the peer-reviewed scientific research evaluating Noom and a review of the features included in the Noom Weight intervention.

Chapter 3 : Noom Weight Loss Coach: A Case Study

Introduction

Chapter 3 Synopsis

To date, there is a lack of published case studies that have reviewed the literature pertaining to Noom, and there has not been a quality assessment of the features integrated in the 2017 update. This case study provides a background of the development of Noom, which is now an industry leader in mHealth weight loss and diabetes prevention interventions. A literature review has shown that Noom's personalized coaching, evidence-based curriculum, and digital tools effectively promote sustainable behavior changes related to weight loss. Studies have demonstrated the utility of Noom for successful weight reduction, which increased significantly with the increased input of self-monitoring of diet, exercise, and weight. The evidence provided by the growing body of scientific research suggests that Noom has the potential to achieve significant short- and long-term weight loss. This case study also provides a review of Noom's evidenced-based mHealth strategies that were identified in chapter 2. There is sufficient evidence surrounding the use of BCTs, gamification, EMIs and EMAs, and online social networks. Overall, this case study suggests that Noom is an effective mHealth weight loss program that incorporates evidence-based strategies which could lead to the successes identified in the literature review.

Background

Noom was founded in 2008 by Artem Oetakov and Saeju Jeong, who were passionate about building an affordable and scalable healthcare solution that would address chronic conditions. This passion led to two failed fitness trackers. In 2011, the first iteration of Noom was built around psychological and CBT in their digital weight management tool (Thau, 2021). The AI robots coached users through their weight-loss journey, but even with some of the best AI health-coach technology, the tool alone needed to get customers to change their eating habits. While humans need empathy, love, and compassion, AI tech cannot fully replace people-to-people interactions. In 2017, Noom relaunched and hired full-time, certified human coaches, now at the heart of the business, and the app took off shortly after. In 2018, Noom experienced a growth of 408%, and in 2019 a 288% growth (Thau, 2021). After a $540 million funding round in 2021, Noom expanded beyond its weight loss program to address stress and anxiety, diabetes, hypertension, and sleep (Landi, 2021). In 2021, Noom was valued at $3.7 billion, employing 3,000 people, of whom 2,700 are health coaches. Also reported in 2021, Noom has over 45 million downloads in 100 countries (MacLellan, 2021).

As of 2023, Noom now offers Noom Mood, Noom Weight, and a diabetes prevention program. Subscribing to the Noom Weight platform in March of 2023 costs users $70 a month or $209 a year before taxes (Noom, 2023). The features provided in this plan will be provided later in this chapter. The Noom Mood platform has one subscription plan billed every four months and costs $149, and provides CBT lessons and activities, mood tracking, and a live text-based health coach. The Noom diabetes prevention program is a 12-month course intended for individuals with pre-diabetes. This narrative review failed to find a price for this intervention. According to Noom's latest report in 2023, 40 peer-reviewed scientific papers were published between 2016 and 2023 that examine the effectiveness of Noom's methods in managing various health conditions, including diabetes, weight loss, and cancer. The following section will review the scientific literature surrounding Noom Weight and the Noom Diabetes Prevention Program.

Literature Review of Noom

Noom is an industry leader in weight loss apps, leading to recent scientific research surrounding its innovative approach to weight management and behavior change. This research has shed light on the efficacy of Noom's personalized coaching, evidence-based curriculum, and digital tools in promoting sustainable weight loss and healthy lifestyle habits. There are currently 40 peer-reviewed scientific papers published on various Noom platforms. This narrative review overviews studies on weight loss and diabetes management outcome measures. Studies that only had an abstract available or were observational studies were excluded from the analysis. This review identified twelve papers fitting these criteria.

As mentioned in chapter 1, three landmark quality reviews and content analyses analyzed the most popular weight loss apps on the app store. Since these three studies were published from 2013 to 2016, this narrative review failed to find more recent reviews of today's apps. Chen et al. (2015) was the only study found in this literature review that included Noom within their study. Out of the 28 apps examined in 2014, based on the literature ranking, Noom scored the highest, with 75 points. Most noticeably, the app scored highest in the scientific coverage and accuracy category (28 out of 32), in technology-enhanced features (9 out of 14), and the second highest incorporation of BCTs (14) (Chen et al., 2015).

To investigate the effectiveness of Noom on weight reduction, Chin et al. (2016) used the clinical data of 35,921 Noom users between October 2012 and April 2014. Of the 35,921 Noom users, 77.9% reported a decrease in body weight while using the app for an average of 267 days. BMI changed from 30.2 to 28.1 kg/m2 for males and 28.0 to 26.5 kg/m2 for females, with 22.7% of all app users experiencing >10% weight reduction compared with baseline. The study also identified that increased self-monitoring input of diet, weight, and exercise were critical factors in determining successful weight reduction. The study demonstrated the utility of a mHealth app for successful weight reduction for most app users (Chin et al., 2016). A further paper was published from the archived data from an international community sample of 7,680 overweight men and women, with informed consent, which was used to test a hypothesis that greater self-monitoring adherence would be positively associated with weight loss outcomes. The selected participants began the program between December 2012 and February 2013 and continued the program for over three months. Over three months, an average of 1.92 BMI points were lost. Adherence to self-monitoring did increase weight loss; for every 10% increase in adherence, there was a decrease of 2.59 BMI points (Jacobs et al., 2017).

An additional investigation was conducted to assess the effectiveness of Noom for managing metabolic syndrome components related to weight loss in 104 adults. Participants who signed up for Noom were recruited and received an in-person orientation about the study, app

use, and a baseline blood sample. After 15 weeks, the participants displayed a significant weight loss of 7.5% at the end of the 15-week program, and at a 52-week follow-up, a weight loss of 5.4% was maintained. Percent body fat and visceral fat decreased by $6.0 \pm 5.4\%$ and 3.4 ± 2.7 kg, respectively, at 15 weeks. Besides high-density lipoprotein cholesterol, fasting glucose and lipid parameter levels also significantly improved. The confidence intervals indicate a wide range of metabolic syndrome biomarkers, indicating that results may vary greatly among individual participants. This study highlights the potential effectiveness that the Noom intervention has in improving metabolic outcomes (Tomo-Ramos et al., 2017).

In another article by Tomo-Ramos et al. (2017), 50 adults were recruited into a 24-week Noom intervention pilot study that evaluated the efficacy of a Hypertension Prevention Program (HPP) on metabolic markers. Noom's intervention yielded improvements in weight, diastolic blood pressure, and hypertension, however, the results varied greatly among participants. The pilot study also emphasized that sustained app engagement of 80% resulted in significant weight reductions (3.04 kg to 3.78 kg) and blood pressure reductions (5.06 to 7.75 kg) (Tomo-Ramos et al., 2017). The pilot study showed the short-term potential of Noom to reduce the risk of hypertension, however, longer randomized controlled studies are needed to determine if this effect is significant.

While the pilot study provided promising results, another study revealed a more comprehensive understanding of the relationship between engagement and weight loss outcomes. Carey et al. (2021) extracted and analyzed 11,252 eligible participants from the Noom database to determine the relationship between weight loss outcomes and engagement with Noom. The engagement measures included the number of articles read, messages with the coach, and self-monitoring of meals, steps, and self-reported weight measurements. Multiple linear regressions examined how weight loss outcomes were associated with each engagement measure at 9-16 weeks, 17-32 weeks, and 33-52 weeks. At 9-16 weeks, 23.05% had stable weight, 57.23% had moderate weight loss (between 5-10%), and 19.71% had high weight loss (>10%). By 33-52 weeks, 18.21% had stable weight, 42.11% had moderate weight loss, and 39.68% had high weight loss. The linear regression results showed that moderate and high weight loss outcomes were significantly associated with all engagement measures compared to a stable weight (Carey et al., 2021). This further confirms the literature standard that self-monitoring adherence and user engagement are important for weight loss success in mHealth interventions.

Although the literature cited above is not composed of randomized controlled trial studies, Chin et al. (2016), Jacobs et al. (2017), Tomo-Ramos et al. (2017), and Carey et al. (2021) provided empirical evidence of the relationship between Noom's weight loss intervention and weight loss success. Based on the evidence, Noom can achieve significant short- and long-term weight loss in retrospective cohort studies. In addition, Noom could reduce percent body fat, visceral fat, diastolic blood pressure, hypertension, fasting glucose, and lipid parameters. Adherence and engagement to self-monitoring meals, steps, weight measurements, and communication with the coaches were related to weight loss success. Users already using the app are motivated to change their behavior to address their weight, which is a key limitation of the studies provided. While these results provide valuable insights into the relationship between Noom and weight loss, RCTs are needed to establish causality, especially since motivated individuals might find other avenues to support their weight loss in the absence of Noom. The following papers will overview the RCTs completed from 2017 to 2022, including Noom as an intervention arm for weight loss.

As one of the core features of Noom, nutrition and dietary education and self-monitoring of food intake may help individuals change their eating behaviors. In a randomized controlled pilot study, dietary intake was examined to demonstrate initial evidence of the effects of Noom on changing dietary habits. Forty adult bariatric surgery candidates (82.5% female) were assigned to Noom or standard care. Participants' dietary intake was assessed at baseline and after eight weeks of intervention through a 24-hour dietary recall. The Noom intervention, compared to the control (a nutritional pamphlet), provided significantly greater reductions in empty calorie consumption, total calorie and fat intake, and a lower percentage of fat intake, yet there were no significant changes in macronutrients and micronutrients between groups. These preliminary results appear promising, however, they are from a short intervention (8 weeks) with a small sample size (n=40). Further research is needed to validate these effects on diet in pre-bariatric surgery patients (Kim et al., 2019).

Another randomized controlled trial of 129 participants aged 30 to 59 years, with at least two moderate metabolic abnormalities (defined by the National Cholesterol Education Program), were assigned to the control (n=41), Noom only (n=45), or Noom with in-app personalized coaching (n=43). The control group received baseline education. After 40 weeks, each group showed decreasing systolic blood pressure from baseline with no significant differences among the group. However, Noom with personalized coaching showed greater body weight (-0.96 kg) and body fat mass (-0.79 kg) reductions compared to the control (-0.12 kg, -0.13 kg) and stand-alone Noom interventions (-0.35 kg, -0.64 kg) (Cho et al., 2020). This randomized controlled trial highlights the importance of a personalized health coach in the Noom intervention to reduce body weight and fat mass effectively.

This literature review found two RCTs, Kim et al. (2019) and Cho et al. (2020), that specifically studied the nutritional and weight loss outcomes in the traditional Noom Weight platform. Noom's Diabetes Prevention Program (DPP) is the only fully mobile DPP to receive full CDC recognition. This recognition was given because Noom's DPP program is the only fully mobile program clinically proven successful in peer-reviewed journals. Several preliminary studies surrounding Noom's DPP were published before the RCT. The non-RCT Noom DPP intervention papers by Michaelides et al. (2016), Michaelides et al. (2018), and DeLuca et al. (2020) provided the foundation for possible success in significant weight loss and mixed results for changing blood glucose and HbA1c values over the 16 to 24-week intervention. Increased weight loss was associated with increased self-monitoring, health coach communication, and user engagement.

Toro-Ramos et al. (2020) examined the long-term weight loss and HbA1c of Noom's DPP (n=101) compared to a usual care control group (n=99) in a randomized controlled trial. Noom's DPP intervention provided core content for 20 weeks, additional content for up to 52 weeks, and coaches who communicated in real-time with the participant. The control group received traditional medical care and a paper-based DPP curriculum. Changes in participants' weight and BMI were significantly different at six months between intervention and control groups by −2.64 kg and −0.99 kg/m2, respectively. At 12 months, the Noom DPP program completers achieved a weight loss of 5.6% at six months and maintained a 4.7% weight loss after 12 months. The control group lost 0.15% at six months and gained 0.33% at 12 months. While small, there were significant decreases in HbA1c levels at 12 months, a 0.23% reduction in the intervention, and a 0.16 % reduction in the control. Individuals who completed the Noom DPP program and were engaged with the app demonstrated higher weight loss and HbA1c reductions (Toro-Ramos et al., 2020).

While more research is needed to validate the results of the recent RCTs that use Noom mHealth interventions, the evidence provided by the growing body of scientific literature suggests that Noom has the potential to achieve significant short- and long-term weight loss and improve metabolic outcomes such as body fat, fasting glucose, and lipid parameters. Most studies found that engaged users of Noom reached clinically important weight loss, or more than 5% body weight over 6 to 12 months. Noom's potential efficacy has generated more peer-reviewed literature than any other weight loss program.

Review of Noom's Evidenced-Based mHealth Weight Loss Strategies

The purpose of this case study is to review the evidence-based mHealth features used in effective weight loss interventions. The specific features examined were the same features that were reviewed in chapter 2 which included BCTs, gamification, ecological momentary interactions and assessments, and online social networks. One reviewer interacted with Noom over a 2 week period to determine if the range of features provided aligned with evidence-based mHealth methods through a qualitative approach. However, this design has some limitations. The review is based on a single reviewer's experience with the app, which may not fully represent the experiences of other users. The review did not include outcome measures, such as weight loss and behavior change.

After interacting with Noom for two weeks, the reviewer found that Noom offered a range of features that aligned with evidence-based BCTs, including self-monitoring, goal setting, feedback and rewards, and social support. The app also incorporated these BCTs with gamification elements, such as progress tracking and virtual badges. Additionally, the reviewer found that Noom used EMAs and EMIs to remind users to track self-monitoring of meals, exercise, and weight and provided feedback on the adherence to self-monitoring performance. Finally, the reviewer identified several methods of online social support, including the Noom Circles program and health coach interactions.

Behavior Change Techniques

The literature examined from chapter 2 underlined several takeaways surrounding the use of BCTs. In mHealth-based interventions, the incorporation of more BCTs was found to have a larger effect on behavior than interventions with fewer techniques (Webb et al., 2010). Based on the literature review in chapter 2, Chen et al. (2015) was the only quality review with Noom within the selection criteria. Of the 28 apps reviewed, Noom was the highest-ranked app based on the grading criteria. Noom included the second-highest BCTs (14/26), which included the range of BCTs commonly associated with greater effectiveness (Chen et al., 2015). This quality assessment was conducted in 2014, which predates the re-launch of Noom in 2017. It can be inferred that since 2014, Noom has increased the utilization of BCTs in its program. This can be inferred due to the app's additional human-coaching element added in 2017, which satisfies the qualifications for social learning and social influences BCTs. Additional findings from chapter 2 surrounding BCTs found that techniques congruent with the Control Theory, specifically self-monitoring, goal setting, feedback on performance, and a review of behavioral goals, were significantly more effective than other interventions (Samdal et al., 2017). The reviewer found that Noom incorporated these BCTs by providing users with a way to track their food intake, exercise, and weight. Users could also set daily and long-term goals related to healthy eating habits, physical activity, and weight loss and receive feedback and reminders to help them stay on track. Finally, the app reviewed users' behavioral goals, which allowed for the self-reflection component of Control Theory.

Gamification

Gamification has positively impacted emotions, behaviors, and user experience in mHealth interventions. In addition, it has also been found to improve adherence and motivation for behavior change (Lu et al., 2013). The reviewer found that Noom incorporates multiple gamification techniques, such as rewards, badges, and challenges. In addition, Noom has daily quizzes which offer users a small virtual high-five when the question is right. In addition, Noom shows data in visual formats, instead of telling the user how many steps were completed, the app shows an individual walking down a progress bar toward the daily step goal. The app's various educational programs even have a virtual “adventure map” to show the user's progress. In all, Noom takes advantage of a lot of gamified elements.

Ecological Momentary Interactions and Assessments

EMIs AND EMAs are mHealth interventions that allow real-time tracking and monitoring of behaviors and experiences in the user’s natural environment. EMIs and EMAs are important components with stand-alone success in mHealth weight loss interventions. According to the reviewer, EMAs were utilized in the design of Noom in multiple ways. Noom encourages users to log meals, exercise, and weight daily. The app provides a “goals reflection” overview of the weekly success of self-monitoring the various behaviors. While the reviewer did not complete a personalized coaching session, the description provided by the app’s website highlights that coaches ask users to reflect on their progress and identify potential barriers to achieving their goals. The reviewer found that Noom does not provide a text-message EMI, which is an effective mHealth weight loss strategy, however, it does send notifications through the app and by email. The reviewer concludes that EMIs and EMAs are sufficiently utilized in Noom’s intervention.

Online Social Support

As discussed in chapter 1, social support is an important factor in weight loss interventions and is important for weight loss success (Wang et al., 2014). Although the evidence presented in chapter 2 regarding social media in weight loss interventions was inconclusive, it did suggest that online group therapy could potentially serve as a viable alternative to traditional social support networks, which are effective in in-person weight loss interventions. The reviewer found that Noom provides the ability to connect with a virtual community of other Noom users through a group chat feature called “Noom Circles.” The reviewer found that the Noom Circles are uplifting and motivational. This social support feature allows users to supplement the social support needed in a successful weight loss journey. In addition, Noom provides coaches through both in-app texting services and video calling (for additional purchase), which would also be used as a social support mechanism.

Chapter 3 Discussion

The narrative review summarizes the peer reviewed literature surrounding the efficacy on Noom's approach to weight loss and behavior change. The literature first highlights the effectiveness of Noom through the extracted user data in a retrospective cohort study design. Several studies found that users experience a clinically significant short- and long-term weight loss. Adherence and engagement to self-monitoring meals, steps, weight measurements, and communication with the coaches were related to weight loss success. Nonetheless, a significant limitation of the studies presented is that the individuals who used the Noom app were already motivated to modify their behavior to manage their weight. A few RCTs have been conducted to determine that Noom's approach caused the weight loss. Studies comparing the Noom intervention with a regular treatment control found that Noom's intervention causes moderate short- and long-term weight loss and can improve metabolic outcomes such as body fat, fasting glucose and lipid parameters.

Chapter 3 also analyzed Noom's utilization of evidence-based mHealth behavioral interventions, specifically BCTs, gamification techniques, EMI/EMAs, and online social support. The reviewer found that Noom increased the amount of BCTs since the last quality review was completed by Chen et al. (2015), which reported that Noom had the second most BCTs used among the the 28 apps examined. The reviewer explored the use of gamification techniques such as rewards, badges, and challenges. Additionally, the reviewer discussed the use of EMIs and EMAs in Noom, and specifically noted how Noom encourages users to log meals, exercise, and weigh themselves daily. Lastly, the reviewer found that Noom addresses the importance of social support in weight loss interventions through the virtual community and group chat feature called "Noom Circles", as well as the in-app texting and video calls with the health coaches. This narrative review provides evidence that Noom adheres to the evidence-based mHealth behavioral interventions which could lead to the effectiveness presented by the scientific literature. Additional RCTs are recommended to further build the base of evidence surrounding Noom as an effective weight loss approach.

General Discussion

Limitations

Limitations of this narrative review include the potential for selection bias, as the studies included were selected based on the author's interpretation and selection of the literature. The literature selection process was limited to specific databases: Google Scholar, Web of Science, and PubMed. While most of the research provided in this narrative review was high quality, most of the systematic reviews and meta-analyses included some low-quality studies which could affect the validity of their findings. Additionally, the lack of meta-analyses limits the ability to draw quantitative conclusions. In addition, the review of Noom was completed by one reviewer. The limitations of having a single reviewer lead to the potential for bias and a lack of diversity in perspectives, which can limit the validity and generalizability of the findings from this section. Despite these limitations, the current narrative review provides a useful overview of the literature and highlights areas where further research is needed to strengthen the evidence base.

Discussion

This narrative review of literature discussed in chapter 1 the growing burden of overweight and obesity on the health of the individuals affected, including physical, biological, psychological, and sociological impacts. Evidence surrounding the biological impact suggests that in order to achieve long-term weight loss, individuals should undergo a gradual weight loss over a long period of time to minimize the rebound effect. The chapter also discusses the costly economic and environmental impacts and calls attention to increased public health efforts to enact cost-effective prevention programs. The complex nature of this issue has given rise to various weight-loss management methods, such as modifying nutrition and physical activity, pharmacotherapy interventions, undergoing bariatric surgery, and receiving behavioral interventions. Although these approaches have demonstrated moderate success, calls from national and worldwide public health agencies suggest that all-encompassing behavioral interventions are essential in maintaining weight loss. This comprehensive intervention is time-consuming, costly, and unscalable to reach the large overweight and obese population in need.

Chapter two discussed how the recent smartphone innovation has given rise to a new intervention that could be utilized to solve this problem. mHealth weight loss interventions are accessible, cost-effective, and can be scaled to address the population in need. A further review of the literature provides evidence that mHealth weight loss interventions are effective at achieving clinically significant weight loss, however, certain methods employed in mHealth interventions exhibit superior efficacy. An effective mHealth intervention must deploy features that increase user engagement and app adherence to match the effectiveness of comprehensive and time-consuming in-person behavioral interventions. Increased weight loss from mHealth interventions was associated with additional components outside the mHealth intervention, increased self-monitoring input, and app adherence. Evidence-based strategies in mHealth weight loss interventions underline the importance of BCTs, gamification, ecological momentary interactions and interventions, and online social support. A literature review of the quality of popular apps found that most apps need to include more BCTs, gamification, and social support methods. A front runner among the quality reviews included Noom, which is now the industry leader in mHealth interventions for weight loss.

Chapter three presents a case study of Noom, including an overview of its development as an industry leader in mHealth weight loss interventions through the use of evidence-based mHealth techniques. The chapter also includes a literature review to comprehensively assess the growing body of literature regarding Noom's effectiveness in weight loss, which has yet to be done previously. The review provided evidence that Noom’s techniques effectively promote weight loss, which increased significantly with improved self-monitoring of diet, exercise, and weight. Finally, the case study reviewed how Noom utilizes the evidence-based behavior change techniques identified in chapter 2. The reviewer found sufficient evidence that Noom’s weight loss intervention addressed the techniques identified. However, Noom fails to have a medication reminder which represents a potential area for improvement in the current intervention. The management of overweight and obese populations commonly uses several medications to manage their disease. This case study suggests this feature should be included to address another feature of Noom and other mHealth interventions for weight loss.

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ACADEMIC VITA

NOAH R. WIGGINS

SUMMARY

An undergraduate Biobehavioral Health student focused on health disparities, entrepreneurship, and minimizing barriers to preventative care practices. Currently creating a preventive care company, Preventi, that minimizes barriers to accessing health information and increasing patient medication compliance through a low-tech solution.

EDUCATION

The Pennsylvania State University Class of 2023
Schreyer Honors College
College of Health and Human Development
B.S., Biobehavioral Health
Presidential Leadership Academy Certificate Program at Penn State

EXPERIENCE

Optometrist Technician, Optometric Care Inc., Aliquippa, PA April 2017 – June 2020
-Proficient in diagnostic testing such as Optical Coherence Tomography, Autorefractor, Visual Field Test, Optical Topography, Fundus Photography, Tono-Pen Eye Pressures, and Visual Acuity Testing
-Experienced working with Electronic Health Records and handling patient information with professionalism
-Taught insertion and removal of contacts, and proper care of contacts
-Worked alongside optometrists, assisting them with eye drop insertion, medical scribing, and phoropter testing

Encompass Health Rehabilitation Hospital Volunteer January 2018 - Current
- Assisted eye care practitioners bedside and transcribed into the electronic medical records
- Assisted nursing staff in distribution of water, snacks, and supplies to stroke and neurological disorder patients

Research
- Research Assistant for Dr. Kris-Etherton lab on cardiovascular nutrition 2021 - 2022
- Independent review of "Inequities in Pediatric Cancer Outcomes" 2021 - 2022
- "Computer Vision Syndrome Management and Relief" - First Place Award, Best in Health Sciences 2019

Medical Mission Trips June 2015 & 2017
-Used skills as Optometric Technician to assist doctors in helping hundreds of patients in Honduras
-Collected hundreds of used glasses for patients and village clinic

HealthWorks Peer Educator 2021- Present
-Leading public health talks on sexual health, sleep, nutrition, and stress management to Penn State student body
-Working with current faculty to change dated material and update curriculum

HONORS/AWARDS

Presidential Leadership Academy at Penn State 2020 - Present
Jane B. Slep Honors Scholarship 2020 - Present
-Awarded to Schreyer Honors Students in the College of Health and Human Development
Academic Achievement Award 2020
Princeton Book Prize of Western Pennsylvania 2018
- Outstanding Academic Achievement and Service Award

EXTRACURRICULAR AND LEADERSHIP

Health and Human Development Student Council President 2022 - Present
Serve State Member & Executive Board Member 2020 - 2022
Health and Wellness Advisory Board Member 2022- Present
HealthWorks Special Team Leader 2022 - Present
Co-Founder and Co-President of Health Sciences Club 2017- 2019
Ice Hockey Team Captain 2018 - 2019
Science Olympiad Captain 2012 - 2019
Eagle Scout - Senior Patrol Leader 2012 - 2019