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Developing the *mHealth Framework for Investigating Tailoring (mFIT)* to evaluate the types and dose of tailored information in mobile apps for chronic condition self-management

Committee:

Bo Xie, Supervisor

Yan Zhang

Jacek Gwizdka

Miyong Kim

Neil Charness

William Aspray

Developing a framework to evaluate the types and dose of tailored health information in mobile apps for chronic condition self-management

by

Ivan A. Watkins II

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Developing a framework to evaluate the types and dose of tailored health information in mobile apps for chronic condition self-management

Ivan A. Watkins II, Ph.D.
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Supervisor: Bo Xie

Most older adults in the U.S. suffer a chronic condition such as diabetes, accounting for two-thirds of U.S. healthcare costs. Self-management interventions can improve outcomes for older adults with chronic conditions, and diabetes in particular exemplifies interventions' potential to improve self-management. Problematically, managing chronic conditions involves multiple, complex behaviors. A mobile health (mHealth) approach where older adults self-manage conditions with apps presents a cost-effective solution. However, older adults often lack experience with apps, facing challenges include usability, stress, and privacy. Tailoring may improve self-management by providing information developed for a specific individual based on their characteristics, but the mechanisms of tailoring are unclear.

This study aimed to develop the *mHealth Framework for Investigating Tailoring* Version 1 (*mFIT* V1), which evaluates and quantifies the tailoring types chronic condition self-management apps provide. The tailoring literature informed mFIT V1, which I revised using a sequential, mixed-methods approach with three studies. Study 1 aimed to identify mFIT V1 elements needing revision with a content analysis of diabetes apps using mFIT V1. This study identified five main issues and revisions to address the issues, producing mFIT V2. Study 2 used a survey and individual interviews with older diabetics to identify the tailoring elements

facilitating self-management. A thematic analysis identified themes, including three benefits of mFIT V2, four main issue with mFIT V2, and revisions to mFIT V2 that informed mFIT V3. Study 3 involved a survey and individual interviews with app developers to identify the tailoring elements developers perceive as facilitating self-management. A thematic analysis identified themes that included two benefits for mFIT V3 and three main issues with mFIT V3. I developed revisions addressing these issues, producing mFIT V4.

This dissertation's contributions include identifying challenges older adults face using chronic condition self-management apps, clarifying which mechanisms support tailored apps, and developing mFIT. Conceptual contributions include redefining tailoring and developing the information dose concept. Useful contexts to apply mFIT include evaluating the way tailoring types impact self-management, evaluating commercially available apps, and identifying issues in the tailoring type these apps provide. mFIT can also inform intervention design through decision rules that determine the tailoring types interventions use.

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Chapter 1: Introduction

An estimated 60% to 75% of people in the U.S. endure a chronic condition, such as diabetes, stroke, arthritis, and heart disease, while 81% of adults age 65 and above in the United States suffer multiple chronic conditions (Buttorff, Ruder, & Bauman, 2017). Chronic conditions account for 95% of older adults' healthcare costs (Center for Disease Control and Prevention, 2013), and 90% of all healthcare costs in the United States (Buttorff, Ruder, & Bauman, 2017). Self-management interventions can reduce health complications from chronic conditions, and diabetes in particular can serve as an example of the potential for self-management interventions to reduce health complications.

Problematically, self-managing chronic conditions requires older adults to perform multiple, complex tasks. For instance, the American Association of Diabetes Educators (2018) identified seven key self-management behaviors, including: 1) healthy eating; 2) physical activity; 3) blood-glucose self-monitoring; 4) medication management; 5) problem solving; 6) risk reduction; and 7) healthy coping. Further, older adults with the least education, health literacy, and income likely possess the greatest need for self-management interventions, but interventions are frequently expensive and lack sustainability (Powers et al., 2015).

A mobile health (mHealth) approach, such as using apps to self-manage chronic conditions, presents a potentially cost-effective solution to providing older adults with self-management interventions (Nundy et al., 2014). However, older adults often lack experience, knowledge, or skill with this technology (Neter & Brainin, 2012), and 7potential issues facing older adults using mHealth include usability, stress, and privacy (Hampton, Rainie, Lu, Shin, & Purcell, 2015). Additionally, as older adults often lack experience using mHealth to self-managing chronic conditions, the challenges of a mHealth approach to improving chronic condition self-management for the older population remain unclear.

Tailoring offers a potentially effective approach to self-managing chronic conditions for older adults with diabetes. Tailoring is "any combination of information or change strategies intended to reach one specific person, based on characteristics that are unique to that person, related to the outcome of interest, and have been derived from an individual assessment" (Kreuter & Skinner, 2000, p. 1). Meta-analyses found tailored interventions outperform non-tailored interventions (Krebs, Prochaska, & Rossi, 2010; Lustria et al., 2013). Despite outperforming non-tailored interventions, the challenges of tailoring for older adults self-managing chronic conditions with mHealth remain unclear. Identifying and developing solutions to these challenges in the context of diabetes self-management can inform the broader issue of improving chronic condition self-management for older adults. Potential solutions include developing features for tailored mHealth apps that address these challenges.

The mechanisms by which tailoring improves outcomes remain unclear, despite calls to address this gap (Harrington & Noar, 2012; Hawkins, Kreuter, Resincow, Fishbein, & Dijkstra, 2008; Kreuter, Bull, Clark, & Oswald, 1999). Several factors contribute to the obfuscation of tailoring's mechanisms. First, while tailoring studies use health behavior theories such as the transtheoretical model to develop messages, few theories explain how or why tailoring is effective (Noar, Harrington, & Aldrich, 2009). Second, inconsistent reporting of intervention results limits researcher's ability to compare key intervention characteristics, such as the type and dose of tailoring, and synthesize findings from tailoring studies (Harrington & Noar, 2012; Lustria et al., 2013).

Steps towards overcoming these gaps in the tailoring literature include developing a consensus tailoring definition (Kreuter & Skinner, 2000), a proposed model of tailoring mechanisms called the message effects model (Noar et al., 2009), and proposed reporting standards for tailoring studies (Harrington & Noar, 2012). Despite these efforts, the literature lacks an operational tailoring definition, no known studies evaluate the message effects model, and studies have not adopted the proposed reporting standards. Further, the proposed reporting standards, a set of seven recommendations developed to address inconsistencies in how tailoring studies evaluate and report their findings, conceptualize dose of tailored information only by the amount of tailored information an intervention provides (Harrington & Noar, 2012). Tailoring additional elements of dose, such as the frequency, sequencing, and delivery system, and interactions between different types of information could also impact tailoring's effectiveness (Johnson, 2014). Similarly, the proposed reporting standards only examine three types of tailoring in personalization, feedback, and content matching, excluding potentially impactful tailoring types, such as framing.

Next, the message effects model asserts different tailoring types impact specific constructs, such as attention or perceived relevance, to influence outcomes (Harrington & Noar, 2012). Problematically, no known studies investigate the influence of different tailoring types, or how different tailoring types interact, and this gap derives in part from inconsistency in how studies evaluate the type of tailoring provided by mHealth applications. The proposed reporting standards offer a solution, but tailoring studies have not adopted these standards (Lustria et al., 2013).

Developing a framework to evaluate and quantify the type and dose of tailoring provided by mHealth apps offers an alternative approach with much promise. Such a framework could enable researchers to evaluate the way tailoring different dose elements and types of tailoring impact chronic condition self-management. For instance, researchers could use this framework to investigate the way tailoring for dose and type impacts chronic condition self-management or to better understand the impact of different tailoring types and the interaction of different combinations of tailoring types. Quantifying type and dose also improves the proposed reporting standards, which do not quantify type and dose. Additionally, such a framework more comprehensively accounts for the dose elements and tailoring types than the proposed reporting standards. At this time, comprehensively accounting for dose elements and tailoring types is important because the tailoring literature indicates these factors impact outcomes, but their relative influence remains unknown. As a result, excluding potentially impactful dose elements and tailoring types from the framework could limit the framework's effectiveness.

Following this introduction, Chapter 2 presents a critical literature review of concepts related to mobile app-based tailored diabetes self-management interventions for older adults. Chapter 2 includes three subsections:

1) Diabetes self-management among older adults: this subsection examines the cognitive, motor, sensory, and social changes facing older adults with diabetes, and identifies how these changes impact diabetes self-management. This subsection focuses on diabetes, which serves as an example for chronic conditions in this dissertation.

2) Technology and non-technology based approaches to diabetes self-management: this subsection evaluates technology and non-technology based diabetes self-management interventions, identifying the benefits and challenges of each approach.

3) Tailored approaches to diabetes self-management interventions: this subsection reviews the tailoring literature, first examining the consensus tailoring definition. This

subsection also examines tailoring's mechanisms before evaluating seven gaps related to the type and dose of tailoring.

Chapter 3 presents preliminary work I completed for this dissertation. This preliminary work includes the *mHealth Framework for Investigating Tailoring* Version 1 (*mFIT* V1), which consolidates, evaluates, and quantifies the different tailoring types and dose elements provided by chronic conditions self-management apps.

Chapter 4 presents the research methods which used a sequential, mixed-methods approach with three studies. Study 1 identified the elements of mFIT V1 needing further development with a content analysis of diabetes self-management apps using mFIT V1. This study identified a set of main issues and subsequent revisions to address those main issues. This revision process produced a second version of mFIT called mFIT V2. Study 2 used a survey and individual interviews with older adult diabetics to identify the tailoring elements that support diabetes self-management. I revised mFIT V2 based on the results of study 2 to develop mFIT V3. Study 3 consisted of a survey and individual interviews with mobile app developers. I revised mFIT V3 based on the results of study 3 to develop mFIT V4.

Chapter 5 presents the results. First, the content analysis from study 1 identified a set of five main issues with elements of mFIT V1. To address these main issues, I developed a set of five revisions, from which I developed mFIT V2. Additionally, I identified three benefits of mFIT V1 during the first study. Second, the thematic analysis of the qualitative data collected during study 2 identified major themes. These themes included three benefits of mFIT V2, along with a set of four main issues and ten sub-issues with mFIT V2. I developed a set of four revisions to address these main issues, and developed mFIT V3 through this process. Third, the thematic analysis of qualitative data during study 3 identified major themes that included two benefits for mFIT V3 and three main issues with mFIT V3. To address these main issues, I developed a set of three revisions to mFIT V3. Through this process I developed mFIT V4, which consists of six tailoring elements.

Chapter 6 discusses the contributions this research makes to the literature, which include identifying challenges older adults face in using mHealth apps to self-manage chronic conditions, clarifying the mechanisms that underlie tailored chronic condition self-management apps, and developing the mFIT framework. Additionally, conceptual contributions include defining tailoring and developing the concept for information dose. Theoretical contributions include developing a framework for evaluating the type and dose of tailoring provided by an intervention. Useful contexts to apply mFIT include evaluating the way different tailoring types impact chronic condition self-management, evaluating commercially available apps for chronic condition self-management, and identifying issues in the type and dose of tailoring provided by these apps. mFIT can also inform the design of self-management interventions, and provide a basis for the decision rules that determine which tailoring types to use.

Chapter 2: Literature Review

This chapter presents a literature review examining three key areas related to older adults self-managing their diabetes with tailored mHealth apps. First, I review the literature on diabetes self-management among older adults. This review examines the cognitive, motor, sensory, and social changes that can occur among older adults with diabetes. Second, I review the literature on technology- and non-technology-based approaches to diabetes self-management. This review identifies the potential benefits and challenges of each approach for older adults with diabetes. Third, I review the tailoring literature. This review identifies gaps for defining tailoring, the mechanisms of tailoring, dosage of tailored information, assessing dosage, personalization, feedback, theory-based content matching, and message framing.

DIABETES SELF-MANAGEMENT AMONG OLDER ADULTS

Older adults present the highest prevalence of diabetes among any age group in the United States, with an estimated 25.2% of older adults suffering from the disease (Centers for Disease Control and Prevention, 2017). Despite these high rates, older adults remain the least studied age group of diabetics (National Center for Chronic Disease Prevention and Health Promotion, 2014). This gap stems from the exclusion of older participants with comorbidities or cognitive impairments, such as dementia, from clinical trials (Kirkman et al., 2012). As a result, it remains unclear how age-related cognitive, motor, sensory, and social changes affect self-management (American Diabetes Association, 2014). In this chapter, I review the literature to identify the age-related cognitive, motor, sensory, and social changes that may complicate self-management for older adults.

First, cognitive aging describes age-related changes in cognition that reduce individuals' information processing ability (Park & Schwartz, 2012). Studies on cognitive aging detected a negative, linear relationship between chronological age and cognitive performance, with low variability between age peers. These results suggest a negative relationship between aging and cognition, with changes manifest as declines in attention, memory, processing speed and capacity, difficulties integrating new information, and poor decision-making performance (Mitzner, McBride, Barg-Walkow, & Rogers, 2013; Pachman & Ke, 2012; Van Gerven, Paas, & Tabbers, 2006). Psychosocial factors may also mediate this relationship (Salthouse, 2010). For instance, older adults display a positivity effect, defined as "an observed age-related increase in the preference for positive over negative information in attention and memory" (Reed, Chan, & Mikels, 2014, p. 1). Additionally, older adults can experience improved crystallized intelligence with aging (Zaval et al., 2015). Crystallized intelligence is "an experienced-based component of intelligence that is acquired through interaction with one's environment" (Zaval et al., 2015, p. 152). Such improvements may compensate for declines in fluid intelligence that occur with age (Reijnders et al., 2013; Borella et al., 2010) defined as "reasoning ability, and the ability to generate, transform, and manipulate different types of novel information in real time" (Zaval et al., 2015, p. 152).

Along with age, diabetes is an independent risk factor for cognitive decline in older adults. Older diabetics experience reductions in working memory, executive function, and attention. These declines correlate to adverse health outcomes, such as depression, hypoglycemia, poor treatment adherence (Wong, Scholey, & Howe, 2014), and reduced life expectancy (Bordier, Doucet, Boudet, & Bauduceau, 2014; De Galan et al., 2009). Further, an individual's working memory, attention, and executive function play essential roles for learning (Paas & Ayres, 2014), and older diabetics can experience greater difficulty comprehending sentences than non-diabetic older adults (Cahana-Amitay et al., 2013). Together, these studies indicate aging diabetics may face challenges in learning self-management not present for other age groups.

Second, motor ability is "the ability to make large and small movements with one's body" (Mitzner et al., 2013, p. 303). Motor ability declines with age, as does the ability to learn new motor skills, even controlling for declines in working memory (Trewartha, Garcia, Wolpert, & Flanagan, 2014). These declines may challenge older adults' ability to perform self-management tasks dependent on their motor ability, such as performing physical activity for exercise. Diabetes complications may also affect older diabetics' ability to engage in physical activity. For instance, a quarter of diabetics develop foot ulcers (Trewartha et al., 2014), and clinicians perform almost 73,000 diabetes-related lower limb amputations each year on adults over 20 in the United States (American Diabetes Association, 2014). Similarly, arthritis impacts half of U.S. adults age 65 and over, and an arthritis diagnosis raises the probability of physical inactivity by 30% among older diabetics, controlling for body mass index, chronological age, and gender (Centers for Disease Control and Prevention, 2013). To place this rate in context, only 21% of adults in the United States exercise regularly, with rates decreasing with age (Centers for Disease Control and Prevention, 2014). In conjunction, these studies suggest motor ability declines present challenges to self-management for older adults. For instance, concerns over exacerbating joint damage and pain, combined with a lack of knowledge about the safe type and dose of physical activity, present barriers to engaging in physical activity (Centers for Disease Control and Prevention, 2013).

Third, sensory changes such as visual and auditory impairment may affect self-management. Progressive, age-related hearing decline affects a third of adults ages 65 to 74, and almost half of adults ages 75 and over (National Institute on Deafness and Other Communication

Disorders, 2013). Similarly, visual impairments impact almost one-fifth (19%) of older diabetics (Center for Disease Control and Prevention, 2012). These visual and auditory impairments can limit older adults' ability to learn (Paas & Ayres, 2014; Paas & Sweller, 2014), especially in instructional settings where they cannot choose the delivery medium. For instance, an individual with auditory impairment may have difficulty learning from audio narration. While substituting onscreen text for audio narration offers a potential solution, such a substitution could impose additional cognitive demands on individuals' working memory as they process the additional visual information.

Fourth, social isolation[1] may impact self-management for older adults. Social isolation disproportionately occurs among older adults, impacting approximately a third of community-dwelling adults age 65 and above (Cudjoe, 2018; Nicholson, 2012). Factors impacting social isolation among older adults in the U.S. include male gender, lower socioeconomic status, and being white (Cudjoe, 2018). Further, over one-third (35%) of women and almost one-fifth (19%) of men age 65 and above live alone (Administration on Aging, 2013). Social isolation correlates to worse behavioral, physiological, and mental health outcomes for older adults (Cornwell & Waite, 2009; Shankar, McMunn, Banks, & Steptoe, 2011), and predicts mortality at similar rates to clinical risk factors such as smoking and hypertension (Pantell et al., 2013). Behavioral outcomes include reduced physical activity (Hawkley, Thisted, & Cacioppo, 2009;

[1] Social isolation is "a state in which the individual lacks a sense of belonging socially, lacks engagement with others, has a minimal number of social contacts and they are deficient in fulfilling and quality relationships" (Nicholson, 2009, p. 1346).

Shankar et al., 2011) and impaired self-regulation[2] (Baumeister et al., 2005). Additional outcomes include reduced cognitive function (DiNapoli, Wu, & Scogin, 2014), increased blood pressure (Hawkley, Masi, Berry, & Cacioppo, 2006; Hawkley, Thisted, Masi, & Cacioppo, 2010), and a higher prevalence of hearing loss (Mick, Kawachi, & Lin, 2014).

In turn, social support moderates the burden of diabetes on health and quality of life. Social support lacks a consensus definition, but the diabetes literature defines it as "a perception that one is accepted, cared for, and provided with assistance from certain individuals or a specific group or the realization of actual support received from another" (Strom & Egede, 2012, p. 770). Among diabetics, social support correlates to improved glycemic control, diabetes knowledge, treatment adherence, and wellbeing (Baek, Tanenbaum, & Gonzalez, 2014; Schiotz, Bogelund, Almdal, Jenson, & Williang, 2012; Strom & Egede, 2012). For instance, a recent study found social support moderates the negative impact of depression on self-management (Tovar, Rayens, Gokun, & Clark, 2013). Taken together, these findings indicate social support may attenuate the negative outcomes associated with social isolation and diabetes among older adults.

The American Diabetes Association (2014) published four self-management recommendations for older adults with diabetes, including: 1) giving healthy older adult diabetics similar goals to younger diabetics; 2) relaxing glycemic goals based on individual characteristics; 3) varying treatment for cardiovascular disease for life expectancy; and 4) providing individualized screening and assessment. Since so few studies have included older

[2] Self-regulation is an individual's "effective capacity for altering their behavior so as to conform to externally (socially) defined standards" (Baumeister, DeWall, Ciarocco, & Twenge, 2005, p. 589).

adults, the American Diabetes Association gave these recommendations the lowest rating possible.[3] Resolving the knowledge gaps related to the cognitive, motor, and sensory changes that occur with age can clarify the influence of aging on diabetes self-management, and more broadly, chronic condition self-management. Further, resolving these gaps can help researchers develop interventions that address these unique challenges facing older adults with chronic conditions.

Technology and Non-Technology Based Approaches to Diabetes Self-Management

While few diabetes self-management studies include older adults, researchers studied self-management interventions in younger populations extensively over the past 40 years (Oldenburg, Taylor, O'Neil, Cocker, & Cameron, 2015). Self-management interventions focus on facilitating “the knowledge, skill, and ability necessary for diabetes self-care” (American Diabetes Association, 2015, p. S20) and are effective at improving glycemic control (Chrvala, Sherr, & Lipman, 2015; Qi et al., 2015), increasing knowledge and self-efficacy (Steinsbekk, Rygg, Lisulo, Rise, & Fretheim, 2012), and enhancing quality of life (Sugiyama, Steers, Wenger, Duru, & Mangione, 2015). However, only 7% of diabetics are estimated to participate in self-

[3] The American Diabetes Association rates the level of scientific evidence supporting the recommendations using four grades: an 'A' rating for "clear evidence from well-conducted, generalizable RCTs that are adequately powered"; a 'B' rating for "supportive evidence from well-conducted cohort studies"; a 'C' for "supportive evidence from poorly controlled or uncontrolled studies"; and an 'E' for recommendations based on 'expert consensus or clinical experience" (American Diabetes Association, 2014, p. S15).

management interventions, in part because insurance companies often fail to reimburse participants for the financial costs of participation (Powers et al., 2015). This percentage is likely even lower for older adults, whose cognitive, motor, sensory, and social changes discussed in the prior section can present barriers to participation. Technology and non-technology-based approaches to diabetes self-management interventions offer solutions but differ in their benefits and challenges. In this section, I evaluate non-technology and technology-based approaches to diabetes self-management interventions, and also identify the benefits and challenges with each approach.

Non-technology based approaches to diabetes self-management

Non-technological approaches to diabetes self-management rely on a combination of expert-led interventions conducted by healthcare providers and peer support interventions (Powers et al., 2015). Both expert and peer support interventions address factors influential to self-management, such as self-management knowledge, health literacy, social support, and cultural needs (Powers et al., 2015). An example expert-led intervention conducted by a bilingual nurse practitioner provided Korean-American diabetics with instruction on seven fundamental diabetes self-management behaviors during two sessions held at a community center classroom (Choi & Rush, 2012). The first session lasted 1.5 hours, while the second session occurred two weeks later and lasted 2.5 hours. Instruction focused on educating individuals on self-management in the relevant cultural context. For instance, when discussing diet, the instruction focused on foods and dishes common to Korean cuisine. This intervention produced statistically significant decreases in blood glucose levels (Choi & Rush, 2012). This significant decrease is consistent with studies using a similar intervention approach with

Chinese-Americans (Sun, Tsoh, Saw, Chan, & Cheng, 2012) and Mexican-Americans (Vincent & Pasvogel, 2007).

Along with expert-led interventions, peer support uses "support from a person who has experiential knowledge of a specific behavior or stressor and similar characteristics as the target population" (Dennis, 2003, p. 329). Prominent peer support models include peer coaching and community health workers (Qi et al., 2015). An example peer coach intervention provided support to low-income diabetics at health centers run by the San Francisco Department of Public Health (Rogers, Hessler, Ghorob, Vittinghoff, & Thorn, 2014). Interventionists recruited coaches from health centers and required them to present controlled diabetes and speak English or Spanish. Training for coaches included components on diabetes self-management skills and knowledge, active listening, social support, and non-judgmental communication. Over six months, bi-weekly meetings between peer coaches and participants centered on identifying challenges to self-management and developing a plan to achieve the participant's self-management goals. This study predicted participants closer in age, ethnicity, gender, or socioeconomic status to their coach would better monitor glucose than participants not sharing characteristics with their coach. However, the most effective coaches presented higher levels of diabetes distress and lower self-efficacy than participants. An explanation was these coaches possessed greater motivation to change their behavior, which may have improved their coaching (Rogers et al., 2014).

Similar to peer-coaching, community health worker programs use lay individuals to provide instruction and support to diabetics in the community (Palmas et al., 2015). Lay instructors share the culture and language of the community, but do not necessarily have diabetes (Qi et al., 2015). An example community health worker program, the Mexican-American Trial of Community Health Workers, trained Spanish-speaking Mexican-Americans from the community to provide diabetes self-management instruction (Rothschild et al., 2012). Community health workers provided individual instruction on seven key diabetes self-management behaviors and five general skills (problem-solving, journaling, adapting the home to support behavior change, obtaining social support, and stress management) during 36 home visits over two years. A protocol dictated intervention content, but workers adapted the content's sequence for individual needs (Rothschild et al., 2012). This intervention produced significant, longitudinal improvements in blood glucose and social support, but found no effect on diet and blood glucose self-monitoring (Rothschild et al., 2014).

Next, non-technology based interventions can draw on a mix of expert-led, peer support, and community health worker approaches to provide interventions. An example of interventions using a mixed approach include The Starr County Border Health Initiative, which provides self-management interventions for diabetic Mexican-Americans living along the border between Texas and Mexico (Brown et al., 2011). The expert-led component of this intervention used nurse practitioners and dieticians to provide instruction on self-management activities through two-hour sessions that met weekly for three months (Brown, Dougherty, Garcia, Kouzekanani, & Hanis, 2002). The peer support component of the intervention involved family members and friends of participants conducting informal, two-hour, bi-weekly support group sessions that lasted for three months. These sessions enabled participants to discuss their concerns and issues with self-management, the effect of diabetes on their family, and included cooking demonstrations and problem-solving components. This intervention produced significant, longitudinal reductions in blood-glucose and improvements in diabetes knowledge (Brown et al., 2002).

Meta-analyses and reviews indicate non-technology based diabetes self-management interventions may be more effective than technology based interventions at improving blood glucose levels (Pillay et al., 2015; Ricci-Cabello et al., 2014), but these reviews do not specify the technology used by these studies. A meta-analysis of 132 randomized controlled trials of diabetes self-management interventions found studies producing significant improvements in blood glucose level relied mostly on in-person delivery, rather than technology or a mix of technology and in-person approaches to deliver interventions -0.31 (95% CI -0.42 to -0.21) (Pillay et al., 2015). This meta-analysis applied three categories, in-person, mix of in-person and technology, and technology only to describe how interventions delivered content, but did not specify the technology used by these studies. Similarly, a meta-analysis of 37 randomized controlled trials of diabetes self-management interventions for ethnic minorities found the interventions effective for improving blood glucose management -0.31 (95% CI -.48 to -.14) (Ricci-Cabello et al., 2014). This analysis also found in-person interventions produced larger reductions in blood glucose than telecommunication-based interventions -0.37 (95% CI -0.62 to -0.12) (Ricci-Cabello et al., 2014). Participant's lack of experience or literacy with technology may explain the telecommunication-based interventions' lower effectiveness. This analysis did not specify the technologies used to deliver interventions. Further, neither Pillay et al. (2015) nor Ricci-Cabello et al. (2014) evaluated whether interventions tailored information, although the Ricci-Cabello et al. (2014) did sample a tailored study.

Although relatively effective, non-technology based interventions can be expensive and lack sustainability. Expert-led interventions require specialized nurses or educators to support self-management interventions, which are expensive and less available in communities with low-socioeconomic status (Bodenheimer & Pham, 2010; Hass et al., 2012). Peer support approaches, such as community health workers, offer a potential solution, but it remains unclear whether these programs are cost-effective (Rush, 2012; Whitley, Everhart, & Wright, 2006). For instance, a randomized controlled trial evaluating a community health worker led intervention in Mexican-American community in Dallas, Texas reduced inpatient hospitalizations. However, the intervention cost $403 per-person, exceeding the $137 savings produced by the reduced utilization of hospital services (Schmidt et al., 2015). The expense of non-technological interventions is a major factor influencing the sustainability of peer support interventions, as these programs rely on inconsistent grant funding and contracts for support, and terminate without funding (Martinez, Ro, Villa, Powell, & Knickman, 2011; Powers et al., 2015). However, technology-based interventions, explored in greater depth below, may present similar issues for older adults with diabetes that require instruction on using technology platforms.

Technology based approaches to diabetes self-management

Similar to non-technology-based interventions, technology-based interventions may also rely on experts or peers to provide support, guidance, and instruction on diabetes self-management. However, technology-based interventions, such as those that use tablets or smartphones, can automate interaction with participants by applying algorithmic decision rules to guide interaction and determine the content participants receive (Sadasivam et al., 2016). Automation may reduce the need for experts or peers to provide intervention content or interact with participants, but it may also require additional technical support. Expert-based, peer support, and automated technology-based interventions offer a number of potential benefits, but also raise distinct challenges. In this section, I first present examples of different approaches to technology-based interventions, and then evaluate the benefits and challenges of each approach to technology-based interventions.

The tablet-aided behavioral intervention effect on self-management skills (TABLETS) provides an example of an expert-led, technology-based diabetes self-management intervention (Lynch, Williams, Ruggiero, Knapp, & Egede, 2016). The TABLETS intervention provided 30 African-American participants in Charleston, South Carolina with a tablet computer and three devices for recording biometric measurements. During this intervention, participants used an app to videoconference with nurse health educators, who provided instruction on diabetes self-management. This app enabled nurses to share instructional slides with participants, and included a whiteboard function which nurses could use to provide visual aids of basic mathematical computations related to diabetes self-management. Additionally, participants used the biometric devices to record their weight, glucose, and blood pressure each day. These devices automatically transmitted readings to a database. Participants could access their readings using the tablet, which presented readings in either a visual or tabular format. In turn, the nurse educators sent participants email messages based on their readings. For instance, a message might say "we should try to improve your blood glucose today" if a participant's blood glucose level fell out of the target range. The researchers' rationale for using mHealth apps to communicate with participants included increasing the intervention's reach to underserved minority populations, which may otherwise face challenges accessing experts. A pilot study for this intervention was in progress at the time researchers reported on this intervention, with researchers planning to evaluate the intervention in a large scale, randomized controlled trial (Lynch et al., 2016).

Next, a mHealth intervention using an interactive voice response system provides an example of a peer-based intervention using technology (Aikens, Zivin, Trivedi, & Piette, 2014). With interactive voice response, users answer pre-recorded questions using the keypad on their mHealth device. A computer processes these responses with an algorithm that determines which response to provide. In this intervention, the interactive voice response system called participants (*N* = 303) from Veterans Affairs clinics in the Midwest each week for 5-10 minutes to query them on their blood glucose self-management, symptoms of hypo- or hyperglycemia, medication adherence, blood pressure, and foot condition. During calls, the system responded with positive reinforcement, such as "Great job, examining your feet each day is key for diabetics." Additionally, participants selected a friend or family member that did not live with the participant to receive email updates on the participant's responses, and to provide motivational interviewing and social support. The system also notified a clinician if participants submitted abnormal blood glucose or blood pressure readings. The study evaluating this intervention found the system effective at improving access to self-management support between scheduled visits with clinicians. However, this study did not assess individuals' A1C, so the impact on that factor remains unknown (Aikens et al., 2014).

Next, automated mHealth interventions do not use experts or peers to provide interventions or interact with participants (Quinn, Khokhar, Weed, Barr, & Gruber-Baldini, 2015). An example of an automated mHealth intervention used a mHealth app to provide seven older adult participants with virtual personalized coaching that provided participants with tailored information intended to educate and motivate participants on diabetes self-management. Over the course of four weeks participants located in Baltimore, Maryland recorded their biometric data, such as physical activity, blood glucose levels, and carbohydrate intake, with the app. The app responds to participants with automated educational or motivational messages, such as "…hope your holidays were good. I notice that you are entering lots of data and that's great" (Quinn et al., 2015, p. 456). The app used an algorithm to provide such messages, drawing on a library of over 1,000 messages designed to motivate and instruct participants on diabetes self-management, functioning as a virtual coach for participants. The algorithm used professional guidelines as the basis for decision rules, but researchers did not describe which guidelines the algorithm used. If participants encountered issues with the app, or required additional assistance, they could communicate with a case manager by email or an online patient portal. This study found that participants' self-efficacy for diabetes self-management increased from baseline, but this increase was not statistically significant (Quinn et al., 2015).

The benefits of technology-based interventions include cost-effectiveness, improved intervention fidelity, and the tracking, communication, and decision support features of mobile apps. First, technology may facilitate more cost-effective diabetes care by increasing the efficiency of care. A recent quasi-experimental study of 348 individuals with diabetes (M = 52.8; SD = 9.2) found a mobile phone-based intervention generated a statistically significant reduction of $32,388 (8.8%) in the cost of care over six months (Nundy et al., 2014). This study included individuals with diabetes eligible to participate in a self-management program at a medical facility affiliated with the University of Chicago. The treatment condition received text-messages prompting participants to perform certain self-management behaviors, such as checking glucose. Additionally, in the treatment condition participants received messages asking questions related to a behavior, such as "do you need refills of any of your medications?" (Nundy et al., 2014, p. 266). The frequency of messages varied for individual preference, and nurses received alerts if patients failed to respond to messages or did not perform an important behavior, such as taking medication. In this situation, nurses conducted a telephone-based, structured assessment of the participant. This technology-based approach enabled fewer nurses to treat more individuals, and improved clinical outcomes with patient satisfaction rates. These efficiencies generated a $32,388 (8.8%) reduction in the cost of care. However, these savings did not include prescription drug costs or fixed program costs, such as technology and staff costs. As a result, actual cost reductions likely fall below the 8.8% estimate provided by the study (Nundy et al., 2014). Additionally, precise accounting of costs is key, as demonstrated by a large scale trial that detected a negative return on investment for a chronic condition telemedicine intervention conducted in the United Kingdom (Henderson et al., 2013).

In addition to cost-effectiveness, mobile apps can help individuals track information related to managing their diabetes. Tracking blood glucose is a key self-management behavior recommended by the American Association of Diabetes Educators (2018), and mobile apps enable individuals to track their blood glucose level, carbohydrate intake, medication, or physical activity (El-Gayar, Timsina, Nawar, & Eid, 2013). Individuals can manually input information or rely on automated features, such as blood glucose meters that transmit information via Bluetooth to mobile apps (Arnhold, Quade, & Kirch, 2014). Benefits associated with using mobile apps for tracking include convenience, especially for individuals that carry their smartphone with them throughout the day (Dennison, Morrison, Conway, & Yardley, 2013)[4]. Additionally, tracking features enable individuals to compare their behavior to their self-management goals (Dennison et al., 2013). Concerns related to tracking with apps include

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[4] Smartphone use by older adults increased from a prevalence of 13% in 2013 to 42% in 2017 (Anderson & Perrin, 2017), and climbed again to 46% in 2018 (Jiang, 2018). Distinct generational differences also exist, with 67% of baby boomers born adopting smartphones in comparison with 30% of the silent generation (Jiang, 2018). It remains unclear the degree to which older adults that use smartphones carry them throughout the day.

making errors when manually inputting information (El-Gayar et al., 2013), forgetting to input information, and becoming demotivated by unmet self-management goals (Dennison et al., 2013). Additionally, while tracking features are consistently the most common feature of commercially available self-management apps (Arnhold et al., 2014; Chomutare, Fernandez-Luque, Ardand, & Hartvigsen, 2011; Goyal & Cafazzo, 2013), no known large scale trials have examined tracking's impact on self-management.

Along with tracking, apps facilitate communication with healthcare providers, caregivers, peers, and family members regarding self-management (Chomutare et al., 2011; El-Gayar et al., 2013). Information collected during tracking can be shared with these experts or peers through email or social media[5] (Dennison et al., 2013). Additionally, social media offers an opportunity to locate and connect with peers or communities that share similar barriers to self-management[6]

[5] The percentage of adults over the age of 65 using social media increased 150% between 2009 and 2011, making older adults one of the fastest growing groups to adopt the medium (Madden & Zickuhr, 2011). This trend continues, with 34% of older adults now using social media, and 47% of older adults those ages 65-69 now using social media (Anderson & Perrin, 2017). These statistics reflect social media's increasing role in how older adults communicate and share information, especially among the baby boom generation.

[6] Social media may also generate key benefits for older adults in addition to improved self-management. Online interaction can provide social opportunities for older adults with disabilities that limit their travel and mobility (Guo et al., 2005), and serve as a venue for providing emotional support (Xie, 2008). Further, social media can strengthen offline relationships for older adults, which can decrease loneliness (Ballantyne et al., 2010). Social

(Chomutare et al., 2011). One challenge facing peer support interventions is the potential lack of sufficient peers in a community (Qi et al., 2015). Apps that connect peers via social networking sites can potentially help address this issue, but few apps integrate social networking site features (Chomutare et al., 2011; El-Gayar et al., 2013) and users may have privacy concerns about sharing personal health information[7] (Dennison et al., 2013).

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media also offers a leisure activity that expands social networks and facilitates psychological well-being (Nimrod, 2010). Last, online communities may help older adults cope with offline networks that diminish in size over time (Nimrod, 2011). Social media can also create opportunities to access and communicate health information. Health applications of social media include communicating with physicians (Hawn, 2009), participating in disease-specific social networking sites groups (Greene et al., 2010), or learning about clinical trials (Swan, 2009). Some social media websites, such as DailyStrength, provide forums for exchanging emotional support (Swan 2009), while PatientsLikeMe lets members exchange advice based on publicly disclosed personal medical data (Frost and Massagli, 2008).

[7] Further, privacy concerns may impede social media adoption by older adults (Lehtinen et al. 2009). Privacy concerns exist because users typically share large amounts of personal information through social media (Ji et al., 2010). Concerns among older adults include access to personal information, along with strangers viewing and distributing photographs. Despite these privacy concerns, older adults are the least likely group of Internet users to limit personal information online (Madden & Smith, 2010). Further, the percentage of older adults taking action to limit the availability of personal information decreased from 28% in 2006 to 20% in 2009 (Madden & Smith, 2010).

Next, mobile apps include decision support features that use algorithms to interpret data to provide individuals with feedback (Goyal & Cafazzo, 2013). Decision support features can provide recommendations on insulin dosage, carbohydrate consumption, or physical activity (El-Gayar et al., 2013). An important advantage of using mobile apps for decision support is that individuals may carry their smartphone with them, so apps can provide real time support that draws on contextual information, such as an individual's location, time of day, social interactions, or activity level, to provide support (Dennison et al., 2013). Additionally, decision support can reduce errors in calculating insulin dosage by eliminating the need for individuals to perform mental calculations for dosage (Huckvale, Adomaviciute, Prieto, Leow, & Car, 2015). However, a review of 46 commercially available apps that provide decision support for insulin dosage found apps contain design issues that could make such apps potentially dangerous. This review found 91% of apps did not validate users' input and that 59% of apps performed calculations even when key information, such as carbohydrate intake, was missing (Huckvale et al., 2015). These errors can result in incorrect dosage calculations that could recommend individuals to take too much insulin.

In addition to the tracking, communication, and decision support features of mobile apps, technology-based interventions can improve intervention fidelity by limiting opportunities for human error (Oldenburg et al., 2015). Intervention fidelity lacks a consensus definition (Dabbs et al., 2011), but can be defined as "the extent to which an experimental manipulation has been implemented as intended, in a comparable manner to all participants" (Taylor, Weston, & Batterham, 2015, p. 2). Studies with low intervention fidelity compromise internal validity by introducing unidentifiable variability into their results (Bellg et al., 2004). Web-based technology can deliver standardized intervention content, such as multimedia tutorials, e.g., Xie

(2011), that individuals can view or interact with on a personal computer or smartphone. Further, portable devices in particular can push information to users through alerts and reminders, while web-based techniques passively wait for users to access information themselves.

Along with benefits, technology poses challenges of stress and privacy. Recent evidence suggests social media causes stress by increasing individuals' awareness of stressful events in others' lives, a phenomenon known as the "cost of caring" (Hampton et al., 2015). Interventions using social media, such as some peer support interventions, could make individuals more aware of these risks and increase their stress level. Similarly, privacy also poses challenges for technology-based interventions, as over a fifth (21%) of Internet users in the United States had an online account compromised (Rainie, Kiesler, Kang, & Madden, 2013), and a 143 million adults in the United States had their information compromised by Equifax (McLannahan & Cornish, 2017) . While 86% of individuals have attempted to conceal their identity online, older adults are the least likely cohort to take these steps (Rainie et al., 2013). A potential explanation is that older adults may lack the knowledge and experience necessary to protect their identity online (Rainie et al., 2013).

Next, low eHealth literacy may challenge older adults participating in technology-based interventions. eHealth literacy is the "set of skills and knowledge that are essential for productive interactions with technology-based health tools" (Chan & Kaufman, 2011, p. e94), and requires health, information, scientific, media, computer[8], and Internet literacy (C. Norman

[8] Computer literacy is the “basic knowledge, skills, and attitudes needed by all citizens to be able to deal with computer technology in their daily life” (Tsai, 2002, p. 69). Although technology’s

& Skinner, 2006). Higher age correlates to lower health and eHealth literacy (Kutner, Greenberg, Jin, & Paulsen, 2006; Neter & Brainin, 2012), so older adults may lack the knowledge, skill, or experience to self-manage their diabetes with technology. Low health

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rapid evolution changes the skills necessary for computer literacy (Hoffman & Blake, 2003; Smith, Schlozman, Verba, & Brady, 2009), participation in contemporary society often demands up-to-date computer literacy. The ability to use computers can encourage civic and political participation (Jaeger & Xie, 2009; Smith et al., 2009; Xie, 2008a, 2010), social engagement (Hampton et al., 2011; Xie, 2008b, 2008c, 2010), and facilitate access to health information (Fox, 2011b; Xie, 2009). Additionally, computer literacy provides a foundation for other literacies, such as eHealth literacy (Norman & Skinner, 2006). Computer illiteracy poses major challenges to older adults' use of mobile devices for self-managing chronic conditions such as diabetes. In the United States, only 59% of adults over 65 use the Internet, compared with 91% of adults age 18-29 (Smith, 2014). Further, only 47% of those over age 75 use the Internet (Smith, 2014), and those with limited economic resources (Chu, Huber, Mastel-Smith, & Cesario, 2009), ethnic minorities (McNeill, Puleo, Bennett, & Emmons, 2007), or those with less formal education (Grimes, Hough, Mazur, & Signorella, 2010) have lower computer literacy levels as well. Other barriers include a lack of Internet access among older adults (Zickuhr & Smith, 2013) and a perception of the Internet as difficult to use (Zickuhr, 2013). Additionally, almost two-thirds of adult, non-Internet users perceive they would need help to start using the Internet, a number that is likely even higher among older adults (Zickuhr & Smith, 2012). These statistics demonstrate the importance of computer literacy in the context of using social networking sites to manage a chronic condition such as diabetes.

literacy limits individuals' ability to navigate the health care system and participate in decision-making (Kobayashi, Wardle, Wolf, & Wagner, 2014), and adults age 65 and above with low health literacy use the internet significantly less than those with higher levels of health literacy (Levy, Janke, & Langa, 2014). In the context of using technology to manage diabetes, low eHealth literacy could lead to worse outcomes. For instance, individuals may receive inaccurate feedback if they make errors when inputting their dietary information.

In sum, technology offers a potentially effective strategy for diabetes self-management for older adults, but few self-management interventions include older adults, making the challenges they face unclear. For instance, a recent meta-analysis of 13 randomized controlled trials of diabetes self-management interventions for older adults conducted from 1980 to 2013 detected statistically significant reductions in blood glucose (Sherifali, Bai, Kenny, Warren, & Ali, 2015), but this analysis contained several key limitations. Only 5 of the 13 studies possessed strong methodological rigor, indicating these studies may contain biases (Sherifali et al., 2015). Additionally, most studies occurred outside of the United States in countries such as Iran, China, Korea, and Belgium, so findings may not generalize to older population in the United States. Notably, this meta-analysis did not evaluate technology's role in these trials.

In contrast, a sub-group analysis conducted as part of the Pillay et al. (2015) meta-analysis found that diabetes self-management education interventions produced no significant difference in blood glucose for older adults. However, this analysis focused on diabetes self-management education, rather than diabetes self-management more generally, and sampled studies did not focus exclusively on older adults, but rather sampled participants with a mean age of 65. This analysis did not examine the role of technology for older adults participating in the interventions (Pillay et al., 2015). Taken together, the Sherifali et al. (2015) and Pillay et al.

(2015) analyses demonstrate the need to clarify the effectiveness of technology and non-technology based diabetes self-management interventions for older adults. Specifically, it remains unclear how the challenges identified by this review, such as privacy, security, and low eHealth literacy, impact older adults.

While few diabetes self-management interventions examine older adults, an expert evaluation of the usability of diabetes self-management apps for adults age 50 and above found most apps rated between moderate and good for usability (Arnhold et al., 2014). This expert evaluation examined 66 diabetes self-management apps using criteria similar to the Nielsen (1994) usability heuristics. This criterion included four categories (comprehensibility, presentation, usability, general characteristics), with two or three specific sub-criteria included in each category. Examples of sub-criteria include "sufficient color contrast" (Arnhold et al., 2014) and "instant and easily understandable feedback" (Arnhold et al., 2014, p. e104). Three experts rated each sub-criterion with a 5-point Likert scale, and experts rated most sub-criteria as moderate or good. All 66 apps received the highest rating on the "use of understandable semantics" (Arnhold et al., 2014, p. e104) and "simple comprehensibility and interpretability of displayed images and depictions" (Arnhold et al., 2014, p. e104) while apps performed worst on the sub-criteria for fault tolerance and "simple recognizability of click-sensitive areas" (Arnhold et al., 2014, p. e104). The results indicated apps did not accommodate mistakes when older adults enter data, and that apps did not make it clear to older adults that onscreen items can be clicked (Arnhold et al., 2014, p. e104). Similarly, a heuristic evaluation of five apps for promoting health eating among older adults identified numerous issues related to onscreen items, including unlabeled advertising, unfamiliar symbols, and icons that use symbols or text that do not indicate the function performed by an icon (Watkins, Kules, Yuan, & Xie, 2014).

SUMMARY

This section examined the benefits and challenges of non-technology and technology based interventions for diabetes self-management. Specifically, these interventions used either technology or non-technology based approaches to interventions. Technology-based approaches included interventions guided by experts, peer-support, or automation. Non-technology-based approaches include interventions guided by experts or peer-support. Non-technology based approaches are relatively effective at improving blood glucose levels (Pillay et al., 2015), with non-technology based peer support approaches effective at providing social support (Rothschild et al., 2014). However, non-technological, expert-based interventions are expensive and require access to experts, suggesting their lack of sustainability can generate issues. Likewise, non-technological peer support interventions often lack sustainability due to inconsistent funding (Powers et al., 2015). Further, the cost-effectiveness of non-technological peer support interventions remains unclear (Rush, 2012; Whitley et al., 2006).

The benefits of technology-based interventions include the tracking, communication, and decision-support features of mHealth apps, cost-effectiveness, and intervention fidelity. Further, mHealth apps can connect diabetics with experts or peers that may otherwise be difficult to reach (Lynch et al., 2016), while automated interventions do not require experts or peers. However, technology-based approaches present distinct challenges. These approaches require eHealth literacy, creating potential issues for older adults, who possess lower eHealth literacy levels than other age groups (Kutner et al., 2006; Neter & Brainin, 2012). Likewise, privacy poses challenges for these technology-based interventions, especially among older adults (Rainie & Smith, 2013). Also, technology-based interventions that rely on social networking sites could increase stress as participants become aware of their peers' stress (Hampton et al., 2015). While technological expert-based interventions require fewer costly experts such as nurses to provide interventions (Nundy et al., 2014), this approach may cost more than peer support or automated approaches that do not require continued expert involvement. Technology-based interventions may also require technical support for older adults, especially for those less experienced or skilled with a particular technology.

Table 1 below compares non-technology and technology based approaches to diabetes self-management.

Table 1: Technology and non-technology-based diabetes self-management interventions

Intervention Approach	*Benefits*	*Challenges*
Non-technology based interventions		
Expert-led	• Effective at improving blood-glucose levels.	• Expense of using experts. • Requires access to experts.
Peer support	• Provide social support effective at improving blood-glucose levels.	• Cost-effectiveness unclear. • Lack sustainability. • Requires access to peers.
Technology based interventions		
Expert-led	• Ability to connect with experts in other areas. • Tracking, communication, and decision support features of mHealth apps. • Cost effective	• Requires eHealth literacy • Privacy • Expense of using experts
Peer support	• Ability to connect with peers in other areas. • Tracking, communication, and decision support features of mHealth apps. • Cost effective	• Requires eHealth literacy • Privacy • Stress caused by increased awareness of peers' stress

	• Intervention fidelity	
Automated	• Tracking, communication, and decision support features of mHealth apps. • Do not require experts or peers • Cost-effective • Intervention fidelity	• Requires eHealth literacy • Require technical support • Privacy

TAILORED APPROACHES TO DIABETES SELF-MANAGEMENT: GAPS

Tailoring can potentially improve older adults' diabetes self-management with mobile apps, e.g., Kim and Seo (2014); Radhakrishnan (2011); Weymann, Harter, and Dirmaier (2013), and meta-analyses indicate tailored interventions outperform non-tailored interventions (Direito et al., 2014; Krebs et al., 2010; Lustria et al., 2013). Despite evidence for tailoring, the mechanisms supporting tailoring remain unclear, an issue described with the metaphor of a 'black box' e.g., Noar, Benac, and Harris (2007), Harrington and Noar (2012), Kreuter and Wray (2003), Abrams, Mills, and Bulger (1999). Opening this black box to review the mechanisms supporting tailoring can lead to more effective tailored interventions by enabling researchers to understand the way different types and doses of tailored information impact chronic condition self-management.

Several factors contribute to the mechanisms of tailoring remaining unclear. First, many tailoring studies use theory to develop tailored messages, but few studies test whether these theories explain why tailoring is effective. Researchers posit the elaboration likelihood model can explain tailoring's mechanisms (Lustria et al., 2013; Noar et al., 2007), and researchers proposed the message effects model to explain tailoring (Noar et al., 2009). Likewise, the motivation and opportunity as determinants (MODE) model offers a theoretical foundation for tailoring (Fazio, 1990). Problematically, few studies evaluate the way these models can explain tailoring, despite calls for such research (Krebs et al., 2010; Lustria et al., 2013).

Second, inconsistent reporting of tailoring study results limits researchers' ability to identify and compare key characteristics of these interventions, such as the type and dose of tailored information used by an intervention. To address this issue, researchers proposed reporting standards for tailored interventions (Harrington & Noar, 2012), and developed a consensus definition for tailoring (Kreuter & Skinner, 2000). The functions of the standards include promoting transparency, enabling readers to evaluate the internal and external validity of tailoring studies, and supporting synthesis of findings through meta-analyses and systematic reviews (Harrington & Noar, 2012). These standards elaborate on the American Psychological Association's journal article reporting standards (JARS), which offer guidelines for reporting empirical research. To develop the proposed reporting standards, Harrington and Noar (2012) developed an initial list of ten recommendations that extended the JARS recommendations, presented this preliminary list to experts at an international conference, and then revised the standards to produce a final list of seven recommendations.[9] Despite the proposed standards'

[9] These recommendations include: "1) some variation of 'tailor' in the manuscript title, abstract, and keywords; 2) specify variables/constructs used for intervention messages; 3) describe how theory informed intervention message design; 4) describe the type of tailored messages participants receive; 5) describe the tailoring system algorithms; 6) describe tailored intervention channel, format, dosage, and context; 7) describe intervention implementation and assessment schedule." (Harrington & Noar, 2012, p. 4-8).

potential, inconsistent reporting persists (Lustria et al., 2013), and gaps in understanding tailoring's mechanisms remain.

Against these gaps, researchers continue to develop tailored interventions with new technologies, such as mobile apps. The tailoring literature divides technology into three generations, where first generation interventions deliver tailored information by print (Skinner, Campbell, Rimer, Curry, & Prochaska, 1999), second generation use interactive, web-based media (Oenema, Brug, & Lechner, 2001), and third generation interventions use mobile devices (G. J. Norman et al., 2007). Problematically, each generation adds features that complicate efforts to describe and identify influential factors (Lustria et al., 2013). Further, tailored interventions using novel technology typically test whether an intervention is effective, not why it is effective (Noar et al., 2009). In turn, because tailoring's mechanisms remain unclear, interventions using new technology lack theoretical guidance. Together, these issues depict a pattern where researchers develop tailored interventions with new technology but make little progress theorizing tailoring's mechanisms. The remainder of this section identifies key gaps in the literature.

Tailoring lacks a consensus definition

The health communications literature defines tailoring as "any combination of information or change strategies intended to reach one specific person, based on characteristics that are unique to that person, related to the outcome of interest, and have been derived from an individual assessment" (Kreuter & Skinner, 2000, p. 1). Consensus for this definition coalesced through a set of editorials published in *Health Education Research* between 2000 and 2001 in response to confusion caused by increasing variation in how studies defined tailoring (Kreuter & Skinner, 2000). Despite criticisms, this definition enjoys continued use in studies evaluating tailored interventions (Kreuter et al., 1999), systematic reviews (Lustria, Cortese, Noar, & Glueckauf, 2009; Radhakrishnan, 2011), critical reviews (Noar, Harrington, Van Stee, & Aldrich, 2011), and meta-analyses (Lustria et al., 2013).

Two characteristics distinguish tailoring from other types of health communications under this consensus definition (Kreuter & Skinner, 2000). First, interventionists design tailored information and strategies for individuals, but develop targeted information and strategies for groups. Second, the tailoring process assesses individuals on individual-level factors, whereas targeted interventions conduct group-level assessments to identify group-level factors influential to attitudinal and behavioral constructs (Kreuter & Skinner, 2000). Kreuter and Skinner (2000) clarified the differences between tailoring and targeting under the consensus definition using two studies as examples. The first study exemplified targeting with a cancer screening intervention that provided educational booklets to Hispanic women residing in San Francisco's Mission District (Perez-Stable, Otero-Sabogal, Sabogal, & Napoles-Springer, 1996). The Spanish-language booklets titled *Mujer y el Cancer* depicted Hispanic models, included testimonials from the Hispanic community, and addressed fatalistic attitudes towards cancer common to Hispanics. By adapting intervention content to a group's characteristics (female Hispanics in the Mission), this intervention exemplified targeting (Kreuter & Skinner, 2000).

The second study exemplified tailoring with a mammography promotion intervention (Skinner, Strecher, & Hospers, 1994). At baseline, investigators surveyed women ages 40 to 65 years old never diagnosed with breast cancer ($N = 435$) by telephone. This survey assessed participants' beliefs of mammogram screening, breast cancer risk status, and barriers to mammogram screening, along with demographic data on age and race. Investigators measured survey answers on a 5-point likert scale, entered the results into SAS, and then transferred data to an ASCII file. This file produced text adapted for each individual based on their survey answers (Skinner et al., 1994). Five months after the baseline survey, participants received letters from their physician with tailored text, along with an illustration of a woman adapted for age and race. In contrast with the targeting example, which developed one booklet for a group, the process from this study could potentially produce 391,000 letters with distinct content. Notably, this process produces identical letters only if individuals submit identical responses on the baseline survey (Kreuter & Skinner, 2000).

Critics of the consensus definition argue it sets arbitrary boundaries for differentiating between different types of health communications. This critique contends tailoring and targeting constitute the same process, but differ only in their degree of segmentation[10] (Hawkins et al., 2008). Originating in economics, segmentation identifies subgroups in a population, assesses their needs and preferences, then develops products addressing those needs (Smith, 1956). Applied to health interventions, segmentation identifies subgroups influenced by similar psychosocial factors related to a desired outcome, such as diabetic adults over the age of 65 (Hawkins et al., 2008). Using this segmentation concept, Hawkins et al. (2008) argued tailoring and targeting are identical types of health communication:

> No matter how many individual attributes are assessed, or whether the measures are demographics or individually reported motives, messages are not in fact written for each individual but targeted for members of that general 'segment'- individuals with similar knowledge, attitude, efficacy, barriers, behavioral pattern, etc. (p. 456).

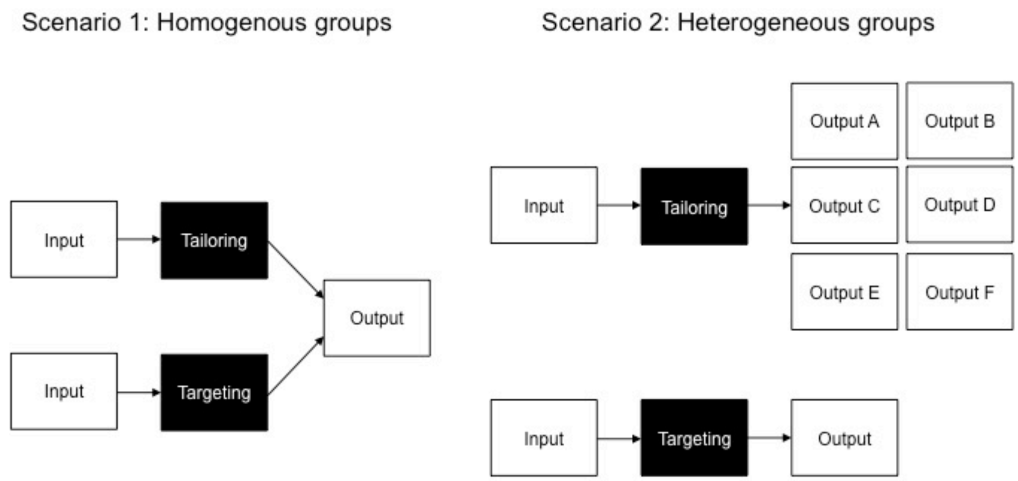
[10] Segmentation is "the practice of defining one's audience into homogenous subgroups that are internally similar yet differ from one another" (Noar et al., 2009, p. 74).

From this perspective, the consensus definition relies on the inaccurate premise that each individual receives a unique communication as the outcome of the tailoring process.

These criticisms conflate the process of tailoring with the output of that process. While tailoring and targeting constitute distinct processes, they can produce either distinct or identical output. For instance, in the second example study, if the individuals presented identical characteristics, the letters they received would be the same as if interventionists conducted a group level assessment. Conversely, for heterogeneous populations, the tailoring and targeting processes produce distinct output. Figure 1 below illustrates this point in two hypothetical scenarios. In the first scenario, individuals present homogenous characteristics, so tailoring and targeting produce identical output. In the second scenario, individuals present heterogeneous characteristics, so the tailoring and targeting processes produce distinct outcomes[11].

Figure 1: Two scenarios for tailoring and targeting processes

[11] Web-based intelligent tutoring applies tailoring in an educational context. Intelligent tutoring systems are "computer-based instructional systems that seek to provide one-on-one tutoring to students based on the science of learning and artificial intelligence techniques" (McLaren, DeLeeuw, & Mayer, 2011, p. 70). This process constitutes tailoring by matching educational content to a learner's knowledge level based on an individual level assessment.



As a pragmatic consideration, the requirement that individuals present unique characteristics creates confusion because interventions often focus on populations with shared characteristics, especially when investigating a specific health issue. For instance, the second example study sampled women ages 40 to 65 years old that lack a breast cancer diagnosis. This cohort likely shares biological, psychosocial, and cultural characteristics. Under the consensus tailoring definition, such a cohort qualifies as tailoring or targeting depending on researchers' interpretation of the consensus definition. These inconsistent interpretations not only create confusion, e.g., Hawkins et al., (2008), Kreuter & Skinner, (2000), but also make operationalizing tailoring difficult.

Confusion with the definition of tailoring also stems from a failure to define the concept of information. Information plays a vital but unexplored role in tailoring, appearing in the consensus tailoring definition (Kreuter & Skinner, 2000), and proposed tailoring models (Noar et al., 2009). Information goes undefined in these contexts, so the relationship between information and tailoring remains poorly articulated. Problematically, definitions for information vary by field, with diverse definitions extant in information science, mathematics, economics, biology, and communications (Floridi, 2010; Zins, 2007). Given this lack of consensus, defining information in relation to tailoring may clarify the definition of tailoring.

The mechanisms supporting tailoring remain unclear

Tailoring studies typically use variables from behavior change theory to match intervention content to individuals' information needs, a process called content matching (Harrington & Noar, 2012). The content matching type of tailoring[12] emerged from the transtheoretical model, which asserts individuals' progress through six stages of change to modify behavior: pre-contemplation, contemplation, preparation, action, maintenance, and termination[13] (Prochaska & Velicer, 1997). At each stage, individuals can use a mix of ten different processes of change, or "activities individuals engage in when they attempt to modify problem behaviors" (Prochaska, DiClemente, & Norcross, 1992, p. 1107)[14]. In this type of

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[12] The literature alternates between the use of type, strategy, and approach to describe content matching. For the purpose of this paper, I use the word type.

[13] Pre-contemplation occurs when an individual has no intent to change behavior; contemplation describes an intent to change behavior within 6 months; preparation describes an intent to change behavior within one month; action describes individuals that changed behavior over the past 6 months; maintenance describes individuals that have not relapsed to prior behaviors over the past 60 months; termination describes when individuals lack motivation to return to their prior behavior (Prochaska & Velicer, 1997).

[14] Processes of change include consciousness raising, self-reevaluation, self-liberation, counter-conditioning, stimulus control, reinforcement management, helping relationships, dramatic relief, environmental reevaluation, and social liberation (Prochaska, DiClemente, & Norcross, 1992).

tailoring, interventionists adapt message content so individuals receive information on the processes of change best matched to their stage of change.

In addition to the transtheoretical model, content matching studies often apply other behavior change theories to develop tailored messages (Lustria et al., 2013), such as the health belief model (Janz & Becker, 1984), theory of planned behavior (Ajzen, 1985), or social cognitive theory (Bandura, 1998). These studies adapt message content for how individuals score on constructs with a theory-based relationship to an outcome of interest (Noar et al., 2011). Meta-analyses confirm content matching consistently outperforms non-tailored interventions, e.g., Krebs et al. (2010); Lustria et al. (2013); Noar et al. (2007). However, while content matching offers a theory-based approach to developing messages, it provides no theoretical explanation for tailoring's effectiveness. Developing such theoretical explanations can clarify why tailoring outperforms other approaches.

To address the gap in understanding tailoring's mechanisms, health communications researchers propose the elaboration likelihood model explains tailoring's mechanisms (Hawkins et al., 2008; Lustria et al., 2013; Noar et al., 2009). The elaboration likelihood model is a dual process theory that describes the way persuasive messages alter attitude (Cacioppo & Petty, 1984). The model asserts individuals process information from messages through either a central or peripheral path. Individuals engage the central path when motivated to attend to a message, while the peripheral path engages when individuals lack such motivation. When information is processed by the central path, the cognitive effort devoted to evaluating the message increases, enabling individuals to elaborate, or engage in critical thinking, regarding a message's arguments. Attitude change resulting from elaboration lasts longer, and is more likely to produce behavior change, than when messages are processed by the peripheral path (Cacioppo & Petty, 1984). From this perspective, tailored messages motivate individuals to attend to messages, causing them to process information through the central path. Further, this perspective differs from other approaches, such as the heuristic-systemic model of information processing, which asserts that in addition to the central path, some individuals rely on a heuristic approach and tend to rely on contextual factors, such as information source, to process messages (Hooper et al., 2013).

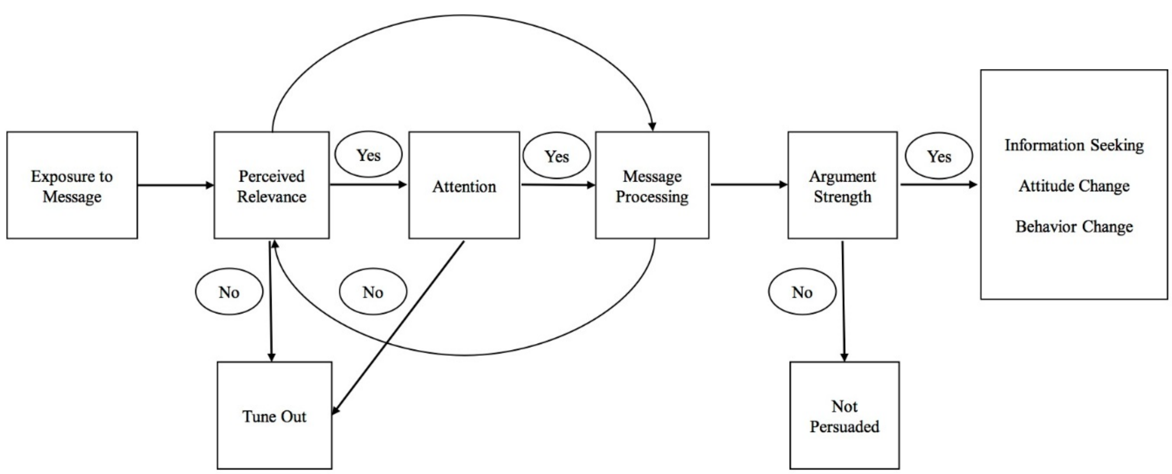
Support for the elaboration likelihood model cites reviews indicating individuals perceive tailored information as more relevant than non-tailored information (Lustria et al., 2013; Noar et al., 2009; Rimer & Kreuter, 2006). This viewpoint asserts motivation to attend to tailored messages increases because individuals perceive tailored information as more relevant than non-tailored information. However, evidence that perceived relevance mediates tailoring's effectiveness relies on systematic reviews and meta-analyses. These reviews found tailored information is more often read, comprehended, recalled, and perceived as credible than non-tailored information (Hawkins et al., 2008; Noar et al., 2009). Along with these studies, researchers have stressed the need for primary studies to evaluate the relationship between tailored information and perceptions of credibility (Kreuter & Wray, 2003; Noar et al., 2009; Rimer & Kreuter, 2006), because no known studies have yet done so.

The motivation and opportunity as determinants (MODE) model builds on the elaboration likelihood model and also provides a theoretical foundation for tailoring (Fazio, 1990). A dual process theory, the MODE model asserts attitude can alter behavior through either deliberative or spontaneous processes. Spontaneous processes can impact behavior without individuals engaging in conscious reflection, relying instead on the immediate activation of individuals' attitude towards a behavior or message. This attitude colors an individual's perception of a message, and functions as a filter through which an individual comprehends a message. In contrast, deliberative processes engage when individuals contemplate their attitudes towards a behavior, and require individuals' time and effort (Fazio, 1990).

The MODE model asserts that individuals require both the motivation and opportunity to engage in deliberative processing. From this perspective, an intervention can tailor messages to increase individuals' motivation and opportunity to deliberate about health behaviors, such as diabetes self-management behaviors. Support for this explanation of tailoring's mechanisms includes a randomized controlled trial comparing three brochures promoting weight loss, including a generic brochure from the American Heart Association, a tailored brochure, and a brochure designed to appear tailored, but contained only generic content (Kreuter, Bull, Clark, & Oswald, 1999). The study consisted of overweight adults ($N = 198$), and found that tailored materials significantly increased the likelihood individuals will deliberate regarding their attitudes towards weight loss (Kreuter, Bull, Clark, & Oswald, 1999). However, no known studies further investigate MODE and tailoring, and MODE provides no evidence for perceived relevance.

Despite limited evidence for perceived relevance, the only known model of tailoring relies on perceived relevance to explain tailoring's mechanisms. This model, known as the message effects model, integrates perceived relevance and the elaboration likelihood model into a five-step path model from the McGuire (1968) model of persuasion. The message effects model begins with exposure to a message, which causes individuals to assess a message's relevance (Noar et al., 2009). If individuals perceive a message as relevant, the probability they will attend to that message increases, catalyzing additional cognitive resources towards message processing. In this context, message processing describes the degree to which individuals elaborate and consider a message. The model hypothesizes a cyclical relationship between perceived relevance, attention, and message processing, such that increases in message processing lead to additional assessments of relevance. Messages compelling enough to support perceived relevance, attention, and message processing lead individuals to elaborate and critically evaluate the strength of a message's arguments. Convincing arguments produce outcomes such as greater information-seeking behavior, attitude change, and behavior change (Noar et al., 2009). Figure 2 below illustrates a path model for the message effects model.

Figure 2: Path model for message effects model, adapted from Noar et al. (2009)



The message effects model posits that different types of tailoring influence specific constructs along the path model. The tailoring literature typically recognizes three types of tailoring in content matching, personalization, and feedback (Harrington & Noar, 2012; Lustria et al., 2009). First, the message effects model asserts content matching influences argument strength by making messages more convincing (Noar et al., 2009). Second, personalization describes "attempts to increase attention or motivation to process messages by conveying, explicitly or implicitly, that the communication is designed specifically for [an individual]" (Hawkins et al., 2008, p. 458). In the message effects model, personalization functions to enhance a message's perceived relevance and capture attention. Third, feedback "provid[es] messages to participants about their psychological or behavioral states" (Harrington & Noar, 2012, p. 336). Notably, the message effects model does not address feedback, a conspicuous omission given feedback's inclusion in proposed reporting standards for tailoring (Harrington & Noar, 2012), and meta-analyses suggesting feedback influences outcomes (Krebs et al., 2010; Lustria et al., 2013).

In addition to the three primary types of tailoring, the message effects model asserts that altering the design, production, and channel of information impacts attention (Noar et al., 2009). To support this assertion, the authors cite a meta-analysis of 57 tailored interventions based on different types of print, such as magazines or letters (Noar et al., 2007). This meta-analysis found interventions using pamphlets and magazines produced significantly larger effect sizes than interventions using letters or booklets. The authors argue this outcome results from the use of visual elements, such as pictures or illustrations, which attract more attention than text-only formats (Noar et al., 2007).

Similarly, the message effects model asserts tailoring the type and structure of information influences message processing (Noar et al., 2009). As an example of this type of tailoring the authors cite message framing, where messages can highlight either the benefits of a behavior, called gain-framing, or the consequences of a behavior, called loss-framing (Gallagher & Updegraff, 2012). According to this perspective, framing a message based on variables such as perceived susceptibility or motivational orientation towards a health behavior can enhance message processing. Table 2 describes the different types of tailoring, outcomes, and variables from the message effects model. Notably, each tailoring type influences a specific outcome, suggesting that including more tailoring types in an intervention can improve outcomes.

However, no known studies have examined the impact of including different tailoring types on outcomes.

Table 2: Types of tailoring, outcomes, and potential variables

Tailoring type	*Outcomes*	*Key variables*
Content matching	Argument Strength	Stages of change, attitude, self-efficacy, social support and processes of change
Personalization	Perceived relevance and attention	Gender, age, race, cultural norms
Adapting design, production, and channel	Attention and message processing	Images, illustrations, video, text
Adapting the type and structure of information	Message processing	Gain vs. loss framing Guilt vs. fear appeals

Information overload not addressed by the Message Effects Model

The message effects model does not explicitly address dose of tailoring information, but implies higher doses improve outcomes by activating cognitive resources. Problematically, the tailoring literature fails to address scenarios where individuals receive too much information, often called information overload. Information overload presents significant issues for tailored self-management interventions, as it can induce stress, anxiety, poor decision making, demotivation (Eppler & Mengis, 2004), poor health outcomes (Bawden & Robinson, 2009; Misra & Stokols, 2011), and poor task performance (Eppler & Mengis, 2004). Further, higher tailoring doses likely require greater effort and expense (Hawkins et al., 2008; Radhakrishnan, 2011), so clarifying the relationship between dose and outcomes could reduce costs and improve outcomes. A potential solution includes tailoring the dose of tailored information an intervention provides, so as to avoid information overload. However, no known studies have examined tailoring the dose of tailored information, and the concept of dose remains undeveloped in this context.

The literature uses the term information overload to describe when too high a dose of information produces negative consequences (Johnson, 2014). Information overload lacks a consensus definition, with research emergent in information science (Bawden & Robinson, 2009), communications (York, 2013), and cognitive psychology (Mayer & Moreno, 2003). Information overload definitions include similar concepts but differ in focus. For instance, a commonly cited definition asserts information overload occurs "when the information processing demand on an individual's time for performing interactions and internal calculations exceeds the supply or capacity of time available for such processing" (Schick & Gordon, 1990, p. 206). According to this perspective, information overload depends on an individuals' ability to perform a task in a set period of time. Negative outcomes associated with this form of overload include poor task performance and decision-making (Eppler & Mengis, 2004)[15].

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[15] Cognitive load theory and a cognitive theory of multimedia learning provide theoretical support for this perspective on information overload in an educational context (Kalyuga, 2007; Mayer, 2005; Van Merriënboer & Sweller, 2005). Cognitive load theory divides human memory into: 1) working memory, which handles small amounts of information for a limited time, and 2) long term memory, which possesses unlimited capacity for information over a long period of time. Information must first be processed in working memory before integration into long-term memory (Baddeley, 2002; Baddeley & Hitch, 1974). Similarly, learning tasks can add intrinsic cognitive load or extraneous cognitive load (Kalyuga, 2007). Intrinsic cognitive load results from the inherent complexity of learning material, while poor instructional design causes

Alternate perspectives on information overload emphasize the perceived experience of overload. From this perspective, information overload describes:

> A perception on the part of the individual or observers of that person, that the flow of information associated with work tasks is greater than can be managed effectively, and a perception that overload in this sense creates a degree of stress for which his or her coping mechanisms are ineffective (Wilson, 2001, p. 113).

This perspective focuses on overload as a catalyst for stress rather than as an impairment to performance. Studies consistent with this perspective found information overload correlates to greater stress and poor perceived health (Bawden & Robinson, 2009; Misra & Stokols, 2011).

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extraneous cognitive load (Sweller, 1994). Reducing extraneous cognitive load decreases demands on working memory, reducing the opportunity for information overload, and improving educational outcomes (Sweller, 1994).

A cognitive theory of multimedia learning extends cognitive load theory to multimedia learning, adding the concepts of dual-coding theory and active processing (Mayer, 2005). Dual-coding theory asserts that learners process information in distinct verbal and non-verbal, e.g., visual, channels (Clark & Paivio, 1991). Active processing explains that learners must actively structure and incorporate learning content with extant knowledge for learning to occur (Mayer & Moreno, 2008). In turn, a cognitive theory of multimedia learning explains that learners must select, structure, and integrate multimedia content into long-term memory for effective learning (Mayer, 2005).

Information overload may impact chronic condition self-management, but few studies have investigated this issue. One study evaluated perceived information overload through 9 focus group interviews with 46 diabetics in a Midwestern city. This study examined how diabetics locate and use health information, and found that post-diagnosis, participants felt the amount and complexity of diabetes information they encountered online served as a barrier to self-management, describing the effect as "paralyzing" (Longo et al., 2010). Similarly, a study assessed a diabetes self-management website's usability through focus group interviews with 23 diabetics website's usability found that perceived information overload would likely decrease website usage (Yu et al., 2014). Notably, one participant described receiving too much information as "getting hit by a car" (Yu et al., 2014, p. 7). Together, these studies suggest information overload can impair self-management.

While few studies examine information overload in the context of diabetes self-management, studies have examined self-management and overload for other health issues, such as maintaining a healthy heart (Crook, Stephens, Pastorek, Mackert, & Donovan, 2015). For instance, a study investigating the relationship between health literacy, perceived knowledge of healthy heart self-management, and perceived information overload used questionnaires to survey 180 participants at a local health clinic in central Texas. This study found that individuals with greater perceived knowledge of healthy heart information were less likely to experience information overload. A potential explanation was that individuals with greater knowledge did not experience overload because their familiarity with the information made it easier to process information. Additionally, this study found no significant relationship between health literacy and information overload. A potential explanation provided by the researchers was that individuals with lower health literacy tend to overestimate their literacy level. This overestimation of literacy may lessen an individual's perception of information overload on self-report measures for information overload. The researchers speculated that a similar result may not occur when using objective measures of information overload (Crook et al., 2015).

Along with information overload, too much tailored information could produce psychological reactance. Psychological reactance is "the motivational state that is hypothesized to occur when an [individual's] freedom [or autonomy is] threatened" (Brehm & Brehm, 1981, p. 37). Reactance can generate cognitive and emotional resistance to performing an action suggested by a message (M. G. Hall et al., 2016). This cognitive resistance is characterized by the development of counter-arguments to a message, while emotional resistance is characterized by anger. Together, these responses can increase an individual's motivation to perform the behavior proscribed by a message, rather than follow a message's suggestions (M. G. Hall et al., 2016).

In the context of health promotion, reactance can cause individuals to defy a message's suggestions (Shen, 2015). For instance, a message recommending someone eat less sugar may lead to reactance if an individual perceives the message as threatening their autonomy to eat as much sugar as they wish. In response, this individual may eat more sugar than before in an attempt to preserve their freedom of choice. The literature describes this result as the 'boomerang effect', meaning individuals engage in the opposite behavior suggested by a health message (David, Henry, Srivastava, Orcena, & Thrush, 2012). No known studies of psychological reactance focus on chronic condition self-management generally, but one study did examine reactance and diabetes self-management (Gardner & Leshner, 2016). This experiment ($N = 58$) found two strategies, narrative and other-referencing[16], attenuated reactance to print diabetes self-management messages promoting diet and physical activity (Gardner & Leshner, 2016). More commonly, reactance studies focus on alcohol, tobacco, or drug cessation, sun tan lotion application, or dental hygiene (Rains, 2012), using brief messages with an explicit, transparent intent to persuade behavior (Shen, 2015).

Investigators examined the relationship between reactance and tailoring in a study on persuading teachers to inform students about CDC flu safety recommendations using tailored video messages (David et al., 2012). This study tailored messages for stage of change from the transtheoretical model. For instance, a message for middle school teachers may state "being a middle school teacher, you have to deal with preteens and teens who have many messages competing for their attention" (David et al., 2012, p. 920). The study randomized teachers to receive either tailored or non-tailored messages, and teachers viewed the video messages online. To assess reactance, the study evaluated message acceptance with a six-item instrument measured on a 7-point Likert Scale. Additionally, the study assessed the tailored messages' effectiveness, teacher self-efficacy to impact students, and behavioral intent to teach flu safety (David et al., 2012).

This study found that teachers in the pre-action stage of change demonstrated significantly greater reactance to the tailored message than non-tailored messages (David et al.,

[16] Other-referencing describes "highlighting the impact of health decisions on family and friends rather than the individual" (Gardner & Leshner, 2016, p. 738), and narrative "describes packaging recommendations as a story rather than as an informational argument" (Gardner & Leshner, 2016, p. 739).

2012). Investigators proposed that the tailored message generated reactance by questioning the teacher's sense of responsibility to their students, along with the teacher's authority in the classroom. For instance, teachers in the pre-action stage with no intent to teach flu safety may have perceived the message as an attack that implies they act irresponsibly towards their students. The investigators also suggest that tailoring may function to amplify negative attitudes generated by psychological reactance (David et al., 2012). For instance, if a personalized message stating "Harold, you need to walk at least 30 minutes per day" generates reactance, the personalization could amplify reactance. This result suggests too much tailoring limits tailoring effectiveness, but future studies must confirm the relationship between dose and psychological reactance.

No approach to assess dose in the tailoring literature

No consensus approach to assessing dose exists, but the proposed reporting standards for tailoring recommended assessing dose by the proportion of tailored information in intervention content (Harrington & Noar, 2012). Under this standard, a web-based intervention with tailored information on one of ten web pages delivers a lower dose than an intervention with tailored information on all ten pages (Harrington & Noar, 2012). In contrast, past approaches assessed dose by the number of tailored messages individuals received or completed. For instance, a smoking cessation study comparing tailored and non-tailored manuals assessed dose by the number of manuals mailed to participants (Velicer, Prochaska, Fava, Laforge, & Rossi, 1999). Similarly, a web-based weight-loss study assessed dose by the number of online modules individuals completed (Verheijden, Jans, Hildebrandt, & Hopman-Rock, 2007). Problematically, these approaches fail to address key elements of dose, including frequency, sequencing, and delivery system.

In the context of information, elements of dose can include amount, frequency, sequencing, and delivery system (Johnson, 2014). A narrative literature review of information overload argued that conceptualizing information dose by amount alone is problematic because it does not assess whether individuals actually consume the information they receive. According to this perspective, assessing information dose by amount alone analogizes to assessing a medication's influence only by assessing amount consumed. Factors such as a full stomach could attenuate or strengthen the medication's effectiveness. Likewise, understanding dose's influence requires consideration a broader range of factors than possible by examining amount alone (Johnson, 2014).

The Health Information Wants Questionnaire (HIWQ) provides an instrument that can be used to tailor amount of information. This instrument evaluates individual preferences for amount of information for seven types of health information, including diagnosis, treatment, laboratory testing, self-care, complementary and alternative medicine (CAM), psychosocial factors, and healthcare providers (Xie, Wang, Feldman, & Zhou, 2013). Additionally, the instrument assesses the degree of decision making autonomy individuals prefer. To evaluate preferences, the instrument includes two sections, one for amount and one for decision making autonomy. Each section uses a distinct, 21-item measure that facilitates comparisons between the two sections, and the instrument uses a 5-point Likert scale to assess the items (Xie et al., 2013). The instrument has demonstrated strong internal consistency, construct validity, and reliability across a number of studies (Xie, Wang, Feldman, & Zhou, 2010; Xie et al., 2013), several of which included older adults (Xie et al., 2010, 2013). One study adapted the framework to evaluate the type of health information provided by a sample of diabetes self-management apps (Nie, Xie, Yang, & Shan, 2016). This study reported agreement rates of over

95% for the two independent evaluators conducting the assessment of the apps, reflecting the framework's strong potential for evaluating amount and type of information for chronic condition self-management apps (Nie et al., 2016).

Next, frequency examines how often individuals receive information (Johnson, 2014). The communications literature indicates repeating messages can enhance a message's influence on attitude and behavior, because it provides more opportunities to consider a message. However, the benefit of repetition may weaken over time (Cacioppo & Petty, 1989), a process analogous to developing a tolerance to a medication (Johnson, 2014). Alternately, the spacing effect indicates temporal gaps in learning content can impact knowledge retention, but the impact of this effect outside laboratory settings remains unknown (Kim, Wong-Kee-You, Wiseheart, & Rosenbaum, 2019). In the context of tailored information, increasing frequency may follow a similar pattern where repetition is initially beneficial, but weakens over time as people grow accustomed to tailored messages and pay less attention to them. While meta-analyses have compared the number of contacts with interventions (Krebs et al., 2010; Lustria et al., 2013), these studies did not assess the frequency of these contacts, and frequency's impact remains unclear. Problematically, no known study assesses frequency in the context of tailoring, and no known instrument, such as the health information wants framework, exists for evaluating frequency in this context.

Along with frequency, the sequence, or order, in which individuals receive information can vary during an intervention (Johnson, 2014). A key feature of stage-based behavior change theories, such as the transtheoretical model, is that individuals pass through a sequence of stages to achieve behavior change. Tailored interventions based on the transtheoretical model provide information based on stage, such that the sequence of information individuals receive reflects their progress through the stages (Antypas & Wangberg, 2014). Likewise, the information search process model asserts individuals progress through six stages to resolve an information need, with each stage characterized by a unique combination of affective, cognitive, and physical states (Kuhlthau, 2010). To promote learning and comprehension, interventions can provide support specific to each stage to aid individuals in resolving their information needs (Kuhlthau, 2010). In conjunction, these models suggest the sequence of tailored information can impact information's influence on behavior.

Next, delivery system describes the means of delivering information (Johnson, 2014). The tailoring literature typically categorizes delivery system by the technology used to deliver information, such as print, telephone, desktop computer, or mobile devices, and divides these technologies into three generations. First generation interventions deliver tailored information by print, such as mailing a tailored letter (Skinner et al., 1999), second generation used interactive, web-based media (Oenema et al., 2001), and third generation interventions used mobile devices (G. J. Norman et al., 2007). While each generation possesses a unique mix of features, this classification system offers little detail on the features actually used in interventions. In contrast, the proposed reporting standards advocated that studies report delivery system by describing channel and format in detail (Harrington & Noar, 2012). Potential channels include print, audio, or video. Numerous formats exist for print alone, including letters, leaflets, magazine, brochures, and calendars (Harrington & Noar, 2012), and contemporary technology, such as mobile apps, can provide information in numerous multimedia formats, including audio narrative, animations, games, and messaging. Understanding how delivery system impacts tailored information could provide guidance for researchers using these technologies to deliver tailored interventions.

The influence of personalization remains unclear

Personalization describes "attempts to increase attention or motivation to process messages by conveying, explicitly or implicitly, that the communication is designed specifically for [an individual]" (Hawkins et al., 2008, p. 458), and may draw on identifiable information, such as name or age (Lustria et al., 2009). The elaboration likelihood model and the message effects model both predict personalization increases perceived relevance and attention towards a message (Noar et al., 2009). Under the proposed reporting standards, three types of personalization appear in the literature: 1) identification; 2) raising the expectation of customization; and 3) contextualization (Harrington & Noar, 2012). Table 3 below provides definitions and example for each type of personalization.

Table 3: Types of personalization, definitions, and examples

Type of personalization	*Definition*	*Example*
Identification	Using an individual's name or other unique identifiers.	Inserting an individual's name or age into the message.
Raising expectation of customization	Making participants explicitly aware that an intervention was designed uniquely for them.	"This system provides you with feedback designed only for you."
Contextualization	Placing messages in a context that is meaningful to individuals.	Integrating cultural images into intervention content.

No known study compares personalization types in the context of health behavior change, but the personalization types do address the lack of clarity in reporting on personalization. Distinguishing types of personalization can help researchers identify the influence of each type, enabling researchers to better synthesize findings through reviews and meta-analyses (Harrington & Noar, 2012). For instance, a systematic review of 30 computer-tailored interventions had difficulty identifying studies using personalization used in a study because it also used elements of feedback (Lustria et al., 2009). In support of this conclusion, the review cited a study that used the second person "you" while providing feedback (Frenn et al., 2005). Under the proposed standards, using the second person can be categorized as raising the expectation of customization, and distinguished from other personalization types.

While the proposed standards for personalization can help categorize types of personalization, researchers did not adopt the standards. For instance, a recent systematic review of 15 reviews on text-based mobile interventions used the terms tailoring and personalization interchangeably (A. K. Hall, Cole-Lewis, & Bernhardt, 2015) as did a tailored smoking cessation study (Dijkstra, 2014). Under the proposed reporting standards, personalization constitutes a specific type of tailoring, so using the terms interchangeably can generate confusion. Similarly, a study used the terms personalized feedback and tailored feedback without clarifying these terms' meanings (Pellegrini, Pfammatter, Conroy, & Spring, 2015). These terminological inconsistencies make assessing the impact of different types of personalization difficult, and limit the ability to synthesize findings on the impact of personalization.

Although no known study investigated personalization types in the context of health behavior change, one study evaluated using personalization type to promote a sports center membership (Maslowska, 2016). This study investigated the three personalization types from the proposed reporting standards (Harrington & Noar, 2012), and predicted personalizing advertisements for a sports center would increase perceived personalization. This study predicted perceived personalization would increase attention towards a message, increasing message processing and creating a more positive attitude towards a message (Maslowska, 2016). Investigators predicted a positive attitude towards a message would occur because personalization increases self-referencing, defined as an individuals' focus on themselves. Self-referencing may evoke positive affect by activating an individual's sense of closeness and familiarity, along with positive thoughts an individual possesses for themselves. These positive thoughts then transfer to positive thoughts about a message (Maslowska, 2016).

To evaluate personalization, investigators developed five versions of an advertisement, including: generic (i.e., no personalization), raising the expectation of customization only, identification only, contextualization only, and a composite version that included all three personalization types. Investigators operationalized perceived personalization with a four-item measure evaluated on a five-point Likert scale. A sample item stated "did you notice personal information in the newsletter?" (Maslowska, 2016, p. 78). Study participants included Dutch undergraduates not part of the university sports center ($N = 285$), whom investigators randomly exposed to one of the five messages online.

This study found the composite and identification personalization types exerted a significant effect on perceived personalization. Further, perceived personalization correlated with increased attention towards a message, along with a more positive attitude for the message (Maslowska, 2016). To explain the lack of effect for raising the expectation of customization, investigators proposed that in the context of an advertisement, individuals may be skeptical towards personalized messages. Similarly, the investigators proposed the contextualized version of the message did not significantly influence perceived personalization because it lacked sufficient distinctiveness to engage self-referencing. Contextualizing for additional factors, such as culture or personality, may be necessary to make a message sufficiently distinct so as to influence perceived personalization (Maslowska, 2016). These findings suggest personalization types differ in their impact on message processing. However, these findings may not generalize to the context of older adults self-managing chronic conditions using mHealth, as this study sampled college-aged students in the Netherlands in a laboratory setting. Additionally, this study investigated personalization in a marketing context, not a health promotion context. To understand if these findings generalize, future studies must evaluate personalization types with older adults using mHealth to self-management their chronic conditions in naturalistic rather than laboratory settings.

The influence of feedback remains unclear

Feedback "provid[es] messages to participants about their psychological or behavioral states" (Harrington & Noar, 2012, p. 336). Whereas personalization increases attention to a message, feedback potentially influences behavioral determinants that include attitude or normative beliefs (Hawkins et al., 2008). The message effects model does not include feedback, despite meta-analyses indicating feedback influences outcomes (Krebs et al., 2010; Lustria et al., 2013), and feedback appearing in the reporting standards for tailoring (Harrington & Noar, 2012). Specific types of feedback include descriptive, comparative, and evaluative feedback (Harrington & Noar, 2012). Definitions and examples for each type of feedback appear in table 4 below.

Table 4: Types of feedback, definitions, and examples

Type of feedback	*Definition*	*Example*
Descriptive	Reporting objective data back to the participant.	"You informed us you never monitor your glucose."
Comparative	Compares an individual's data to their data from a prior point in time or with their peers' data.	"You participated in more physical activity than your peers with diabetes."

Evaluative	Providing judgment or interpretations of participants' data.	"If you do not monitor your glucose, your risk of complications increases."

No known studies compare feedback type, despite reviews identifying a need to better understand their mechanisms (Hawkins et al., 2008; Noar et al., 2007; Noar et al., 2011). However, a critical review discussing tailoring mechanisms proposed a set of potential mechanisms that support each feedback type (Hawkins et al., 2008). This review proposed four mechanisms by which feedback types impact outcomes, including effortful processing, self-referencing, normative beliefs, and attitudes (Hawkins et al., 2008). Effortful processing describes the "careful consideration of persuasive arguments and more systematic utilization of the [individual's] own schemas and memories" (Hawkins et al., 2008, p. 457), and increases the likelihood of processing information with the central route under the elaboration likelihood model (Cacioppo & Petty, 1984). Self-referencing encourages individuals to examine themselves, and also increases the chance of central route processing. Normative beliefs describe "norms governing [the] performance or non-performance of [a] behavior" (Hawkins et al., 2008, p. 458), and attitudes describe individuals' attitude towards a behavior (Hawkins et al., 2008). This review proposed a different mix of mechanisms support each feedback type.

First, the review proposed descriptive feedback's mechanisms include effortful processing and self-referencing (Hawkins et al., 2008). Additionally, descriptive feedback may create a sense of feeling acknowledged or understood among individuals, making them more disposed towards a message (Hawkins et al., 2008). However, the review did not propose specific constructs that capture this sense of acknowledgement and understanding. Second, the review proposed that comparative feedback impacts outcomes by promoting effortful processing, self-referencing, normative beliefs, and attitudes. The review also proposes that comparative feedback can validate beliefs regarding behavior, but provides no empirical support for this claim. Further, the review does not distinguish between comparative-normative feedback, which compares individuals' data to their peers, and comparative-progress feedback, which compares individuals' data to their data from a previous point in time (Harrington & Noar, 2012). Researchers have included these feedback types in interventions for behavior such as bullying (Evers, Prochaska, Van Marter, Johnson, & Prochaska, 2007), but no known study proposes distinct mechanisms support comparative-normative or comparative-progress feedback types.

Third, evaluative feedback may impact outcomes through effortful processing, self-referencing, normative beliefs, and attitude (Hawkins et al., 2008). Evaluative feedback depends in part on making inferences about individuals' perceptions or behavior. For instance, if an individual presents a low score for the perceived benefits of diabetes management, a message may state "you feel there are few benefits to diabetes management." In this example, the message makes an inference about an individual's feelings towards diabetes management. Also, the level of inference can vary between messages (Hawkins et al., 2008). If the above example demonstrates a low level inference, an example of a high level inference message may state, "you do not seem to value your health in terms of your diabetes." This example qualifies as high-level because it makes more general inferences about an individuals' perception of their health. No known studies evaluate the potential influence of inference level (Harrington & Noar, 2012), and Hawkins et al. (2008) proposed that too much inference risks making incorrect judgments.

Although the mechanisms supporting feedback types remain unclear, numerous studies evaluate feedback by the number of assessments used to tailor feedback. Static tailoring describes "providing one baseline assessment on which to base all successive feedbacks" (Krebs et al., 2010, p. 2), while dynamic tailoring describes "assessing intervention variables prior to each feedback" (Krebs et al., 2010, p. 2). Meta-analyses comparing dynamic and static tailoring suggest dynamic tailoring outperforms static tailoring, regardless of delivery method. A meta-analysis of 88 computer-tailored interventions found dynamic tailoring produced significantly greater effect sizes than interventions using static tailoring (Krebs et al., 2010). This meta-analysis aligns with a meta-analysis evaluating 57 tailored print interventions that found number of intervention contacts moderated outcomes (Noar et al., 2007).

In conjunction, the two meta-analyses suggest interventions using multiple contacts, as occurs with dynamic tailoring, will outperform static tailoring. Notably, from the perspective of dose, discussed in gap 2 above, dynamic and static feedback constitute the same type of feedback, differing only in their frequency. From this perspective, the two meta-analyses provide evidence for the effectiveness of higher doses of feedback for the frequency element. A more recent meta-analysis of 40 web-delivered tailored interventions found static tailoring outperformed dynamic tailoring (Lustria et al., 2013), casting doubt on whether higher frequency feedback translates to web-based interventions. However, this finding was not statistically significant (Lustria et al., 2013), and additional evidence is necessary to determine frequency's influence. Likewise, additional evidence is needed to understand the mechanisms supporting each feedback type, and clarify the relationship between feedback and dose elements such as frequency.

The influence of theory-based content matching remains unclear

Despite numerous studies indicating the effectiveness of theory-based content matching, the mechanisms supporting this approach remain unclear (Krebs et al., 2010; Lustria et al., 2013; Noar et al., 2007). The message effects model proposed that theory-based content matching enhances argument strength, making messages more persuasive. In turn, more persuasive messages better promote behavior change (Noar et al., 2009). However, no known studies evaluate whether content matching moderates argument strength, so this approach lacks confirmation, and each behavioral theory proposes distinct mechanisms that support behavior change (Glanz & Bishop, 2010). For instance, the health belief model posits constructs such as perceived threat, perceived benefits, and self-efficacy promote behavior change (Glanz, Rimer, & Viswanath, 2015). The relationship between each behavioral theories' constructs and argument strength remains unknown, as the message effects model does not address the potential role of these constructs.

Next, theory-based content matching can either use all constructs from a theory, some constructs, or mix constructs from different theories. No known review or meta-analysis compares these approaches, and no consensus exists for what qualifies as using a theory 'for' tailoring. For instance, some reviews require that an intervention include each construct from a theory to qualify as using that theory, while other reviews only require that an intervention use some constructs (Noar et al., 2009). This distinction limits researchers' knowledge of the role and influence of theory in content matching, and more broadly, in supporting tailoring's mechanisms. While meta-analyses have examined constructs individually (Noar et al., 2007) and in the context of behavior theories (Lustria et al., 2013), these analyses do not clarify the way each theory's mechanisms support tailoring.

Additionally, researchers typically use only a small selection of theories for content matching (Noar et al., 2009). A recent meta-analysis of web-based tailored interventions found studies most frequently content match using the transtheoretical model, social cognitive theory, and the health belief model (Lustria et al., 2013). Theories used far less frequently include the theory of reasoned action, the theory of planned behavior, social comparison theory, and the precaution adoption process model (Lustria et al., 2013). This meta-analysis counted interventions as using a theory if the study cited that theory as providing guidance for tailoring. Notably, these theories also comprise the three most frequently used theories in health behavior interventions over the past three decades (Glanz et al., 2015).

While researchers know little about the mechanisms supporting content matching, much research investigates the mechanisms supporting theories commonly used to content match. First, social cognitive theory (SCT) asserts behavior change depends on constructs that include knowledge, self-efficacy, outcome expectations, perceived facilitators, impediments and goals[17] (Bandura, 2004). From this perspective, self-efficacy directly impacts behavior, but also indirectly impacts behavior by influencing outcome expectations, goals, perceived facilitators, and impediments (Bandura, 2004). Social cognitive theory positions knowledge as a necessary pre-condition for change, as individuals unaware of the connection between a health behavior and its outcomes possess no incentive to change their behavior. Next, self-efficacy directly impacts behavior as individuals must believe they have an ability to change to affect a behavior change. Self-efficacy also influences outcome expectations, which may include physical outcomes, e.g., weight loss from physical activity, social outcomes, e.g., a spouse approves of weight loss, and self-evaluative outcome expectations, e.g., a feeling of self-satisfaction from

[17] Outcome expectations are "beliefs about the likelihood of various outcomes that might result from the behaviors that a person might choose to perform, and the perceived values of those outcomes" (Glanz et al., 2008, p. 93), while self-efficacy is the "conviction that one can successfully execute the behavior required to produce the outcomes" (Bandura, 1977, p. 193).

losing weight. Likewise, self-efficacy influences individuals' behavior change goals, which can incentivize individuals to change their behavior. Self-efficacy also influences perceived impediments and facilitators, as individuals with greater self-efficacy perceive themselves as more capable of overcoming impediments, e.g., self-efficacy to exercise despite the perceived impediment of a busy work schedule. As a result, social cognitive theory predicts individuals with greater self-efficacy for diabetes self-management better self-manage their diabetes. Meta-analyses and reviews confirm the effectiveness of social cognitive theory for chronic condition self-management interventions (Bandura, 2004; Tougas, Hayden, McGrath, Huguet, & Rozario, 2015).

In the context of tailoring, interventions guided by social cognitive theory can adapt content for individuals' self-efficacy level, goals, outcome expectations, and identified impediments (Bandura, 2004). As noted, numerous studies use social cognitive theory to tailor content, and in particular self-efficacy forms the basis of many tailored interventions (Lustria et al., 2013). Problematically, reviews and meta-analyses typically categorize an intervention as using social cognitive theory even if the intervention only tailors for self-efficacy. This oversight makes it difficult to determine the way other social cognitive theory constructs, such as goals or outcome expectations, might function as tailored interventions. Additionally, it remains unclear if tailoring with social cognitive theory changes behavior by making message arguments stronger, as proposed by the message effects model (Noar et al., 2009), or through the constructs discussed by (Bandura, 2004).

Next, the health belief model predicts individuals' beliefs regarding a health behavior impacts whether they engage in that behavior. This model includes five constructs related to individuals' attitudes and beliefs, including perceived susceptibility, perceived benefits, perceived barriers, and self-efficacy[18] (Janz & Becker, 1984). The model predicts that altering these perceptions alters health behavior, although cues to action may be necessary before change occurs. Cues to action catalyze behavior change and include internal and external cues to action. An example of an internal cue to action includes developing disease symptoms, while an external cue to action could include a public health message broadcast on the radio (Janz & Becker, 1984). When these cues manifest, they can catalyze behavior change.

Content matching plays a key role in interventions based on the health belief model because the model depends on individual perceptions to influence behavior (Glanz et al., 2015). As a practical matter, the model can only impact individual perceptions by providing intervention content that addresses individuals' extant perceptions. For instance, an individual that perceives themselves as a high risk for developing diabetes complications would benefit minimally from messages on the complications of unmanaged diabetes. Reviews and meta-analyses confirm the effectiveness of the health belief model in tailored intervention, including in the context of chronic condition self-management (Jones et al., 2014; Sohl & Moyer, 2007). While these reviews reflect the effectiveness of the health belief model, the specific relationship between the model's constructs remain unknown (Glanz et al., 2015). Likewise, it remains

[18] Perceived susceptibility describes an individual's subjective beliefs about their vulnerability to a health condition, perceived severity describes an individuals' beliefs about the consequences of contracting a health condition, perceived benefits describe an individual's belief regarding the value of engaging in preventative behavior, and perceived barriers describe an individual's belief regarding the negative consequences of engaging in a preventative behavior (Ayers et al., 1997).

unclear if tailoring on health belief model influences outcomes by increasing argument strength, as predicted by the message effects model (Noar et al., 2009).

As noted in Gap 1, content matching emerged from the transtheoretical model, which posits individuals pass through six stages of change by using a mix of ten processes of change (Prochaska & Velicer, 1997). In this approach, individuals receive information tailored to their stage of change and which uses the processes of change. Researchers have confirmed a relationship between stages of change and processes of change, such that certain processes work better for different stages (Prochaska & Velicer, 1997). For instance, consciousness raising, dramatic relief, and environmental reevaluation are most effective for individuals in pre-contemplation or contemplation (Prochaska & Velicer, 1997). However, this relationship lacks consistency with the exception of the decisional balance construct, where individuals balance the pros and cons of changing their behavior. In contrast, researchers detected a mathematical relationship between decisional balance and stage of change, such that the pros of behavior change must increase by twice the rate cons must decrease for an individual to progress to the next stage (Hall & Rossi, 2008). Despite these findings, the relationship between transtheoretical model constructs and argument strength remain unclear in the context of tailoring.

The influence of message framing remains unclear

A critical gap in the tailoring literature is that the mechanisms supporting message framing remain unclear (Rothman & Updegraff, 2010). Message framing applies to messages that convey a health behavior's consequences, with messages framed to emphasize health gains or losses (Updegraff, Brick, Emanuel, Mintzer, & Sherman, 2015). Gain-framed messages focus on the benefits of performing a health behavior, such as monitoring blood glucose. A message may present these benefits as something positive that will likely occur if a health behavior is performed. For instance, a gain-framed message may state, “checking your blood glucose can improve your glucose levels” or “avoiding high fructose corn syrup can lower your dependence on insulin.” In contrast, a loss-framed message emphasizes the negative consequences that may occur from a health behavior. For instance, a loss-framed message may state, “Not checking your blood glucose can raise the risk of diabetes complications.”

The mechanisms that support framing remain unclear (Rothman & Updegraff, 2010), with studies citing prospect theory or the elaboration likelihood model for theoretical guidance. Prospect theory asserts individuals will avoid risks when decisions or actions involve potential gains, but will assume risks when decisions or actions involve potential losses (Kahneman & Tversky, 1979). As applied to health behavior messages, prospect theory suggests loss-framed messages exert greater influence for decisions or actions perceived as risky, while gain-framed messages exert greater influence for decisions or actions perceived as low risk (Bartels, Kelly, & Rothman, 2010; Rothman, Martino, Bedell, Detweiler, & Salovey, 1999).

Framing studies typically bifurcate health behavior into either detection and prevention behaviors, and researchers use these categories to predict the most effective context for gain- or loss-framed messages (Harrington & Kerr, 2016). First, detection behaviors seek to diagnose health conditions among individuals (Rothman & Salovey, 1997). Mammograms and HIV screening provide examples of detection behaviors. Detection behaviors can verify an individual has a serious disease, and the literature typically categorizes detection high risk. As a result, researchers recommend loss-framing messages for detection behaviors. Second, prevention behaviors seek to limit individuals’ risk of developing a health condition. Examples include eating fruits and vegetables, physical activity, or getting a vaccination. The literature categorizes prevention as low risk as these behaviors seek to maintain an individual’s health. In turn, researchers recommend gain-framing messages for prevention behaviors (Rothman & Salovey, 1997).

Meta-analyses of gain- and loss-framing for prevention and detection behaviors provide only limited support for the prospect theory perspective (O'Keefe & Wu, 2012; O'Keefe & Jensen, 2011, 2009, 2007, 2006). For instance, a meta-analysis of framing to promote healthy eating behavior and physical activity detected no significant difference between gain- and loss-framing for healthy eating (O'Keefe & Jensen, 2008). This analysis did find gain-framing outperformed loss-framing for physical activity, showing some evidence for the prospect theory. However, the investigators insisted that prospect theory does not explain gain-framing's advantage for physical activity, citing the results of their prior meta-analyses that did not support prospect theory (O'Keefe & Jensen, 2008). A more recent meta-analysis of 33 randomized controlled trials investigating gain- and loss-framed message for skin cancer prevention (N = 4,168) detected no significant difference between gain- and loss framed messages. Likewise, a meta-analysis of 93 prevention behavior studies (N = 21,656) found gain-framed messages significantly more persuasive than loss-framed studies (O'Keefe & Jensen, 2007). However, 84 of the 93 sampled studies detected no significant difference between gain- and loss-framing. These 84 studies investigated prevention behaviors that included safe sex, healthy eating behavior, and skin-cancer prevention. In contrast, the only studies that found gain-framing outperformed loss-framing all focused on oral hygiene (O'Keefe & Jensen, 2007). In conjunction, these meta-analyses suggest the prospect theory perspective only applies to a limited number of behaviors.

Next, the elaboration likelihood model provides a theoretical foundation for framing (Noar et al., 2009), although fewer studies have examined this theory. As noted above, the elaboration likelihood model asserts the cognitive resources devoted to evaluating information increase when individuals are motivated to attend to a message. This process enables individuals to elaborate and engage in critical thinking about a message, leading to attitude and behavior change (Cacioppo & Petty, 1984). Further, this perspective aligns with the message effects model, which proposes that framing changes behavior by enhancing message processing (Noar et al., 2009). Support for this perspective includes a meta-analysis of 94 framing studies where researchers suggested message processing could mediate the relationship between framing and behavior change (Gallagher & Updegraff, 2012). The researchers proposed this explanation in response to the meta-analysis' findings, which contradicted those predicted by prospect theory.

At present, the influence of tailoring for message framing with chronic condition self-management interventions remains unclear. The message effects model predicts that tailoring the framing of a message influences the way individuals process a message, such that framing may increase the degree to which individuals think critically consider arguments (Noar et al., 2009). The Noar et al. (2007) meta-analysis of print-based tailored interventions found that messages tailored to raise perceived susceptibility significantly lowered effect sizes. A potential explanation for this finding was that messages emphasizing the threat or danger reduce motivation to process a message (Noar et al., 2007). However, this analysis focused on tailoring the content of a message to raise perceived susceptibility, rather than tailoring how a message is framed based on an assessment of perceived susceptibility. Aside from this meta-analysis, no known reviews or meta-analyses of tailoring have evaluated variables related to message framing, so the influence of tailoring a message's framing remains unclear.

CHAPTER SUMMARY

This chapter reviewed the literature in three key areas: diabetes self-management among older adults, technology and non-technology based approaches to diabetes self-management, and tailored approaches to diabetes self-management. Older adults remain the least studied group of diabetics (Kirkman et al., 2012), despite presenting the highest prevalence of diabetes (National Center for Chronic Disease Prevention and Health Promotion, 2014). As a result, it remains unclear how age-related cognitive, motor, sensory, and social changes affect self-management among older adults (American Diabetes Association, 2015). Technology and non-technology based approaches to diabetes self-management interventions offer solutions, but benefits and challenges vary (Pillay et al., 2015; Ricci-Cabello et al., 2014). Specifically, potential benefits include the tracking, communication, and decision-support features of mHealth apps, cost-effectiveness, interventions fidelity, and the ability to connect with remote experts or peers. Common challenges include low eHealth literacy, privacy concerns, and stress. The way these benefits and challenges generalize remains unclear, as few interventions include older adults (Pillay et al., 2015; Sherifali et al., 2015).

Tailoring can potentially improve older adults' chronic condition self-management with mHealth apps (Radhakrishnan, 2011; Weymann et al., 2013), and meta-analyses indicate tailored interventions outperform non-tailored interventions (Direito et al., 2014; Krebs et al., 2010; Lustria et al., 2013). However, the mechanisms responsible for tailoring's effectiveness remain unclear, and the message effects model, the only known tailoring model, remains untested. This model predicts different tailoring types impact specific constructs, such as attention or perceived relevance (Noar et al., 2009), suggesting interventions using more tailoring types better improve self-management by impacting each construct. However, no known studies examine the impact of the number of tailoring types.

Similarly, the literature implies higher tailoring doses improve self-management, but no known studies examine dose's impact. This issue requires examination, as too much information could cause information overload, psychological reactance, or alert fatigue, leading to negative outcomes such as poor task performance, stress, and poor health outcomes. A potential solution includes tailoring the dose of tailored information an app provides, but no known studies have investigated this approach. Problematically, along with a lack of empirical research examining type and dose, inconsistent reporting of tailoring studies makes it difficult to compare these key characteristics of interventions. A set of proposed reporting standards sought to address this issue (Harrington & Noar, 2012), but inconsistent reporting persists (Lustria et al., 2013), and these standards do not fully account for the different types of tailoring, and assess dose by amount alone. Additional elements of dose, such as frequency, sequence, and delivery system may also impact outcomes.

Chapter 3: Preliminary Work

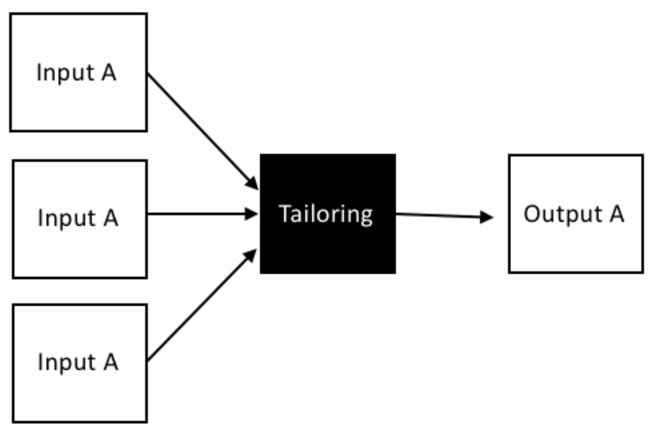
To address the gaps identified in the literature review, I developed the mFIT framework for evaluating and quantifying the tailoring type and dose used by mHealth apps. This framework consolidates and expands on the broad range of tailoring types and dose elements identified in Chapter 2. It provides a comprehensive framework for evaluating and quantifying the tailoring type and dose used by tailored chronic condition self-management apps. In this chapter, I first present a refined definition of tailoring that addresses the limitations with the original tailoring definition detailed in literature review. Second, I explain mFIT's significance, and present useful contexts to apply the framework. Third, I describe how mFIT evaluates and scores apps, including a detailed account for the process used to develop the framework.

REVISED TAILORING DEFINITION

As noted, ambiguities with the tailoring definition make it difficult to distinguish tailoring from other health communications, such as targeting. To address this issue, and more precisely define tailoring, I revised tailoring's definition as part of the preliminary work for this dissertation. The health communications literature defines tailoring as "any combination of information or change strategies intended to reach one specific person, based on characteristics that are unique to that person, related to the outcome of interest, and have been derived from an individual assessment" (Kreuter & Skinner, 2000, p. 1). I edited this definition to remove the clauses "based on characteristics... unique to that person" and the words "change strategies" from the original definition. This revised definition defines tailoring as "any information intended to reach one specific person, related to an outcome of interest, and derived from an individual assessment." This revision provides a more parsimonious definition that contributes to the operationalization of tailoring.

The revised tailoring definition addresses each issue with the original definition identified in Chapter 2. First, the consensus definition required that individuals present unique characteristics to qualify as tailoring, making it difficult to distinguish between tailoring and targeting. By removing the clause, "based on characteristics... unique to that person" (Kreuter & Skinner, 2000, p. 1) the revised definition clarifies that the tailoring process permits individuals to share characteristics. For instance, figure 3 below describes the scenario where three participants present identical characteristics for variables used to tailor information. Because the three participants contribute identical content, each participant receives the same output, described in the figure as ‘Output A’. Under the prior formulation of tailoring, it remained unclear whether this approach constituted tailoring.

Figure 3: Homogenous tailoring input and corresponding output



Second, the revised definition addresses the confusion created by the term ‘change strategies’ in the original definition. As noted in the second chapter, the tailoring literature fails to articulate which type of information the original tailoring definition intended to use, creating confusion. For the purpose of this dissertation, I adopt the concept of semantic information rather than syntactic information, because semantic information most closely aligns with the way researchers conceptualize tailoring[19].

Using this concept of semantic information, "change strategies" can be removed from the tailoring definition. The concept of 'change strategies' derives from the transtheoretical model. These change strategies constitute semantic information, so including change strategies in the definition of tailoring is redundant. As a result, removing 'change strategies' from the consensus definition reduces ambiguity, and offers a more parsimonious tailoring definition.

SIGNIFICANCE

At present, researchers conceptualize tailored information dose as the amount of tailored information an intervention provides (Harrington & Noar, 2012; Velicer et al., 1999; Verheijden et al., 2007). mFIT draws on the information science literature to expand the concept of dose to include elements such as frequency, sequencing, and delivery system (Johnson, 2014). Additionally, I developed two dose elements (event-based, degree of control) based on a preliminary inspection of chronic condition self-management apps. Evaluating these dose

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[19] Semantic information consists of well-formed data which is meaningful, or data that "complies with the meanings (semantics) of the chosen system, code, or language in question" (Floridi, 2010, p. 20). Semantic information is a more specific type of information than syntactic information, which consists of "uninterpreted symbols encoded in well-formed strings of signals" (Floridi, 2010, p. 45). Syntactic information is limited because it does not address whether individuals can comprehend information's meaning. Individuals must comprehend tailored information for it to promote attitude and behavior change, indicating tailored information most closely aligns with semantic, rather than syntactic information.

elements in conjunction facilitates a more comprehensive evaluation of dose than possible under the proposed reporting standards. Further, comprehensively evaluating dose elements is important because the impact of tailoring on different dose elements remains unknown, presenting a key gap in researchers' understanding of tailoring's mechanisms.

Likewise, mFIT consolidates and expands on prior approaches to categorizing tailoring types. Problematically, prior categorizations of tailoring type excluded potentially influential tailoring types that the literature indicates could partly explain tailoring's mechanisms. For instance, the message effect model includes content matching, personalization, and message framing, but excludes feedback (Noar et al., 2009). Similarly, the proposed reporting standards include content matching, personalization, and feedback, but exclude message framing (Harrington & Noar, 2012). Neither study provides an explanation for why they exclude potentially influential tailoring types. In contrast, mFIT includes four tailoring types the literature review identified as potentially influential on the constructs responsible for tailoring's effectiveness. Including these tailoring types in mFIT is essential not only to ensuring a comprehensive assessment of tailoring type, but also to understanding how different tailoring types interact. Additionally, by including these tailoring types, mFIT offers a valuable tool for investigating the influence and interaction between different tailoring types.

Along with comprehensively evaluating type and dose, mFIT quantifies tailoring type and dose for tailored chronic condition self-management apps. Specifically, mFIT produces an unweighted, composite tailoring score for apps that tailor type and dose. These scores are unweighted as no known evidence exists on the relative influence of different tailoring types or dose elements, or the influence of different tailoring type combinations. Under this scoring approach, higher scores indicate an app tailors more types and elements of dose. However, high scores do not necessarily mean an app is more effective, as the impact of each tailoring type and dose element remains unknown. Further, as noted in the literature review, too high a dose of tailoring could lead to information overload, psychological reactance, or alert fatigue, which in turn could add stress, worsen task performance, or generate a negative attitude towards self-management. Developing an instrument that scores tailoring type and dose marks a significant step towards understanding the relationship between tailoring dose and outcomes. Additionally, future research can determine weights for the different tailoring types and dose elements evaluated by mFIT as the impact of these factors clarifies.

Next, the significance of mFIT extends to offering a tool for evaluating mHealth apps. Several studies proposed approaches for evaluating mHealth apps, but these approaches focus on evaluating app quality (Stoyanov et al., 2016; 2015), usability (Healthcare Information Management Systems Society, 2012), and matching patients' needs with chronic condition self-management apps (Hale et al., 2015), rather than assess app characteristics that potentially impact on behavior and health outcomes. An example includes the mobile app rating scale (MARS), which assesses the quality of mHealth apps using five factors, including engagement, functionality, aesthetics, information quality, and subjective quality (Stoyanov et al., 2015). Researchers developed this scale from a literature review that identified 372 criteria used to assess mobile apps. The scale demonstrated reliability when used to evaluate a sample of 50 mHealth apps, and researchers adapted the scale so that lay individuals can use the scale to make their own quality assessments (Stoyanov, 2016).

Similarly, researchers developed a framework that consists of a three-step process for matching chronic condition self-management apps with patient preferences, using diabetes to exemplify a chronic condition (Hale et al., 2015). The first step involves identifying a group of high-quality apps, using an instrument such as the mobile app rating scale (Stoyanov, 2015). In the second step, researchers categorize the strategies used by the apps selected in the first step using the behavioral theory content survey, an instrument that assesses whether interventions use 20 constructs from the health belief model, social cognitive theory, the transtheoretical model, and the theory of planned behavior. In the third step, researchers assess patient preferences through a consultation, taking into account the etiology of their condition and patient motivation. In turn, researchers use these preferences to match patients with apps. Notably, as with the mobile application rating scale, this framework focuses on evaluating the quality of mHealth apps rather than their effectiveness at promoting behavior change (Hale et al., 2015).

Turning from instruments assessing quality, the Healthcare Information Management Systems Society (HIMSS) provides a set of nine usability heuristics for mHealth apps that healthcare providers can use to assess apps, including simplicity, naturalness, consistency, forgiveness and feedback, effective use of language, efficient interactions, and effective information presentation (HIMSS, 2012). In contrast with the mobile app rating systems, these heuristics do not constitute a validated or reliable measurement instrument. Sample criteria include "screen icons, navigation, and email options are intuitive and are consistent with common user applications such as web-browsers" (HIMSS, 2012, p. 24). As with other instruments developed to assess mHealth apps, these heuristics do not assess apps' effectiveness at changing behavior or health, and do not provide an approach for assessing tailoring. Notably, usability dimensions from the human factors provide reliable and valid measures, and include learnability, efficiency, memorability, errors, and satisfaction (Nielsen, 1993).

The utility of mFIT extends to several contexts. First, comprehensively evaluating and quantifying type and dose of tailoring enables researchers to better investigate these factors' influence on self-management. For instance, researchers can use mFIT to evaluate how tailoring different elements of dose (e.g., amount, frequency, sequencing) impacts self-management, or how different tailoring types or combinations of tailoring types impact self-management. Such an investigation can begin clarifying whether too much tailored information leads to information overload, psychological reactance, or alert fatigue. In this context, mFIT improves on the proposed reporting standards by providing an evaluation tool that more comprehensively assesses and scores tailoring type and dose elements.

Second, mFIT offers a tool for evaluating the characteristics of commercially available tailored chronic condition self-management apps. The proposed reporting standards focus on interventions generally, without addressing how the specific characteristics of a technology impact the way individuals interact with tailored information (Harrington & Noar, 2012). Additionally, while the tailoring literature recognizes that technology impacts individuals' interaction with tailored information, e.g., G. J. Norman et al. (2007); Skinner et al. (1999), no known approach to evaluating tailoring addresses a technology's unique characteristics. Each generation of technology used to deliver tailored information adds new features that make it more complicated to identify the tailoring's mechanisms (Lustria et al., 2013), and tailored interventions using new technology most often test whether an intervention is effective, not why it is effective (Noar et al., 2009). mFIT is distinct from prior approaches to evaluating tailoring because I will develop mFIT specific to tailored apps' unique characteristics.

Tailored apps differ from prior generations of technology used to deliver tailored information in key ways. A key difference between mobile apps and earlier technologies is that users often carry mHealth devices with them throughout the day, creating the opportunity to provide users with context-specific, just-in-time tailored information (Rabbi, Pfammatter, Zhang, Spring, & Choudhury, 2015). For instance, an app that detects a user talked on their phone for 40 minutes can provide immediate feedback encouraging the user to walk for exercise during longer phone calls. While print- or web-based tailoring also provide feedback, this feedback is not specific to the individuals' immediate context. Similarly, print- or web-based technologies used for tailoring cannot deliver just-in-time tailored information, with potentially long delays between an assessment and the provision of tailored information. For instance, the physicians in Skinner et al. (1994) took five months after they assessed participants to provide them with tailored letters delivered in print. Given these differences between print-, web-, and mHealth-based technologies, understanding the impact of tailored information provided by apps requires an instrument developed to account for such differences.

Third, mFIT can inform the design of mHealth self-management interventions by providing a basis for the decision rules used to determine which type and dose of tailored information to provide. This feature improves on the proposed reporting standards, which recommend that researchers describe decision rules, but provides no framework to facilitate such a description. In contrast, the framework for tailoring type and dose provided by mFIT can be used to evaluate, describe, or guide the decision rules used by tailored chronic condition self-management apps.

Using mFIT to Evaluate and Quantify Tailoring Type and Dose

In this section I explain the way mFIT evaluates and quantifies tailoring type and dose elements for chronic condition self-management apps. First, I describe the way mFIT categorizes the four main tailoring types and sub-types, and then describe how to code and score these types and sub-types. Second, I explain how to code and score the content matching tailoring type, which uses health behavior theory constructs to tailor content. Third, I explain how to code and score the different elements of dose. Fourth, I present an evaluation form that researchers can use to code and score the tailoring type and dose elements used by a chronic condition self-management app. Fifth, I present a survey questionnaire whose items can serve as the basis for tailoring content in the context of diabetes self-management.

mFIT's Categorization of Tailoring Types

First, mFIT includes four types of tailoring, along with their respective sub-types. I identified these types and sub-types during the literature review presented above. Table 5 below presents each of these tailoring types and sub-types, along with corresponding definitions and examples. These definitions and examples will be used to code and score the type and sub-type of tailored information apps provide. Each subtype receives an unweighted score of one point, so scores for these sub-types can range from 0-10. These scores will remain unweighted for now, but future research can clarify how tailoring types differ in their influence, which could be used to weight scores. Additionally, content matching, which depends on health behavior constructs to tailor content, will be scored using a process described below.

Table 5: Tailoring types.

Type of tailoring	*Definition*	*Example*
Personalization	Messages that convey a communication is designed specifically for an individual.	
Identification	Using an individual's name or other unique identifiers.	Inserting an individual's name or age into the message.
Raising expectation of customization	Making participants explicitly aware that an intervention was designed uniquely for them.	"This system provides you with feedback on your glucose levels designed only for you."

Contextualization	Placing messages in a context that is meaningful to individuals.	Integrating cultural images into intervention content.
Feedback	Messages to participants about their psychological or behavioral states	
Descriptive	Reporting objective data back to the participant.	"You informed us you never monitor your glucose."
Comparative	Contrasts what is known about a participant with what is known about others or themselves.	"You eat fewer fruits and vegetables than your peers."
Evaluative	Providing judgment or interpretations of participants' data.	"If you do not monitor your glucose, your risk of complications increases."
Theory-based content-matching	Developing messages based on theoretical concepts from behavior change theories to influence known behavioral determinants.	"Your risk of developing co-morbidities will increase if you do not manage your diabetes." (This example uses the perceived severity construct).
Framing	Messages describing a behavior's consequences in terms of gains or losses.	

Definitions for personalization and feedback types and subtypes adapted from Harrington and Noar (2012), content matching definition adapted from Lustria et al. (2009), and the framing definition is adapted from Updegraff et al. (2015).

Coding and scoring the content matching tailoring type

Next, to code and score content matching I will evaluate the behavioral theories used to content match. I will code the three most prominent health behavior theories, which include the health belief model, the transtheoretical model, and social cognitive theory. I selected these theories because they comprise the most commonly used theories in both content matching

(Lustria et al., 2013; Noar et al., 2009) and health behavior change interventions more generally (Glanz, Rimer, & Viswanath, 2015; Glanz, Rimer, & Viswanath, 2008; Painter, Borba, Hynes, Mays, & Glanz, 2008; Glanz, Rimer, & Lewis, 2002; Glanz, Lewis, & Rimer, 1990). For the purpose of coding the theories an intervention uses to tailor messages, I will require that interventions use all constructs from a theory. For instance, an intervention coded as using the health belief model must tailor for all of the models' constructs, including perceived barriers, perceived severity, perceived risk, perceived threat, self-efficacy and cues to action. This approach aligns with prior studies that required interventions to include each construct from a theory to qualify as tailoring with that theory (Noar et al., 2009). Further, this approach provides an effective method for distinguishing between theories that share constructs. For instance, both the health belief model and social cognitive theory include self-efficacy. By requiring that theories use all constructs, it becomes possible to distinguish the two theories from each other for the purpose of coding.

Coding and Scoring Dose

Along with type, I will assess the elements of dose that apps tailor, which include amount, frequency, sequence, delivery system, degree of control, and event-triggered information. Three of these elements, frequency, sequence, and delivery system, derive from the literature review presented above. I developed two elements, degree of control and event-triggered information, based on a preliminary inspection of chronic condition self-management apps I conducted while developing mFIT. Definitions and examples for these six elements appear in table 6 below. These definitions and examples can be used to code and score the elements of dose an app tailors. These scores will remain unweighted for now, but future research can determine each dose element's weight. In conjunction, the sum of these items produce a total score for dose that ranges from 0-6.

Table 6: Elements of dose for tailoring

Dose elements	*Definition*	*Example*
Amount	The app tailors the proportion of information it provides.	Three out of five app screens contain tailored information.
Frequency	The app tailors how often an individual receives tailored information.	An app provides tailored information every other week.
Sequence	The app tailors the sequence of information it provides.	The app sequences the information a participant receives based on their stage of change.
Delivery system	The app tailors the modalities used to provide information.	The app uses two modalities to provide information: email and live chat.
Degree of control	The app tailors how much control it gives users over when they receive information.	Users completely control when they receive information.
Event-triggered	The app tailors the information provided when an event occurs.	The app provides tailored information after a user walks for 30 minutes.

Evaluation form for coding and scoring tailoring type and dose

Next, I developed an evaluation form to provide a tool for coding and scoring tailoring type and dose. This form includes a total of 16 items, 10 of which address tailoring type, and 6 of which address tailoring dose. The 10 items for type derive from the sub-types of tailoring described in table 5 above, while the six items for dose derive from the items presented in table 6 above. Each item coded 'Yes' on the evaluation form will receive an unweighted score of one point, producing a total score that ranges between 0 and 16. This evaluation form appears in table 7 below.

Table 7: Evaluation form for coding and scoring tailoring type and dose.

Use this table to evaluate tailored mHealth chronic condition self-management apps. Answer the following questions by placing an "X" in the appropriate column →	Column A	Column B
Type evaluation		
1. Does the app tailor for the identification subtype of personalization?	Yes	No
2. Does the app tailor for the raising the expectation of customization subtype of personalization?	Yes	No
3. Does the app tailor for the contextualization subtype of personalization?	Yes	No
4. Does the app tailor for the descriptive feedback?	Yes	No
5. Does the app tailor for the comparative feedback?	Yes	No
6. Does the app tailor for the evaluative feedback?	Yes	No
7. Does the app tailor using the transtheoretical model?	Yes	No
8. Does the app tailor using social cognitive theory?	Yes	No
9. Does the app tailor using the health belief model?	Yes	No
10. Does the app use gain- and loss-framing?	Yes	No
Dose elements evaluation		
11. Does the app tailor the amount of information it provides users?	Yes	No
12. Does the app tailor the frequency of information it provides users?	Yes	No
13. Does the app tailor the sequence of information it provides users?	Yes	No
14. Does the app tailor the delivery system used to provide information?	Yes	No

15. Does the app tailor the degree of control users have over information?	Yes	No
16. Does the app tailor event-triggered information?	Yes	No
• Assign 1 point to each "X" in Column A for Questions 0-16; • Total the final points, which should range from 0-16; this is tailoring type total:_______________ • Higher scores indicate an app tailors for more types and elements of dose		

CHAPTER SUMMARY

This chapter introduced mFIT, a framework that evaluates and quantifies tailoring type and dose elements for chronic condition self-management apps. First, I explained mFIT's significance, which includes providing the first known instrument for evaluating and scoring tailoring type and dose, expanding the concept of dose from the tailoring literature to include key additional elements, and consolidating and expanding on the types of tailoring used to evaluate tailoring. Next, I described three useful contexts to apply mFIT. These contexts include using mFIT to evaluate and quantify the type and dose of tailoring provided by apps, using mFIT as a tool for evaluating the characteristics of commercially available tailored apps, and using mFIT to inform the decision rules that determine the type and dose of tailored information to provide in interventions. Third, I described how mFIT categorizes four main tailoring types and sub-types, and then explained how to code and score these elements using mFIT. Fourth, I explained how to code and score the content matching tailoring type using 20 constructs from health behavior theories. Fifth, I explained how to code and score the different elements of dose. Sixth, I presented an evaluation form that researchers can use to code and score the tailoring type and dose elements used by a chronic condition self-management app. Finally, I presented a survey questionnaire that can serve as the basis for tailoring on the mFIT elements discussed above.

Chapter 4: Research Methods

This chapter presents the research methods for this dissertation. I first introduce the research questions that guided this dissertation. Next, I present the research methods for this dissertation, including the research design, research sites, participants, measures, materials, procedures, and data analysis.

RESEARCH QUESTIONS

The mFIT framework introduced in Chapter 3 provides a preliminary step in developing a tool for evaluating type and dose of tailoring. mFIT has not been used to evaluate a set of diabetes self-management apps. As a result, it remains unclear what issues with the framework can be identified when the framework is used to evaluate apps. For instance, using the framework to determine if an app tailors frequency may create specific issues if frequency varies subtly over time. This hypothetical issue exemplifies the type of issue an evaluator may face when using mFIT. To begin identifying and addressing such main issues, the first research question asks:

> RQ1: What main issues exist with using the mFIT framework to evaluate tailored diabetes self-management apps?

Next, the preliminary mFIT framework lacks the insight of older adults with diabetes, a key user group. As discussed in chapter 2, older adults differ from other age cohorts in the challenges and benefits they face when using technology, and diabetes self-management requires older adults to perform specific behaviors. Accordingly, incorporating older adults' perspective in the framework can offer vital insight into the tailoring elements they perceive as key to facilitating diabetes self-management. For instance, older adults may perceive that tailoring the time of day an app sends messages facilitates their diabetes self-management. The second research question seeks to address such issues by asking:

> RQ2: Which tailoring elements do older adults perceive as key to facilitating their diabetes self-management?

Similarly, the preliminary framework lacked the insight of mobile application designers. Incorporating designers' perspective can offer valuable insight into the framework's elements, especially when using the framework to guide the provision of tailored information. This perspective differs from older adults' perspective because designer's may possess unique insights into the design and development of tailored diabetes self-management apps as a result of their knowledge, training, and expertise. To begin addressing this issue, the third research question asks:

> RQ3: Which tailoring elements do mobile application designers perceive as key to facilitating older adults' chronic condition self-management?

DESIGN

This research used a sequential, mixed methods design that included three studies. Study 1 conducted a content analysis of diabetes self-management apps which used mFIT V1 to evaluate the apps' use of tailoring. Also, this content analysis identified main issues with mFIT in need of further development. Potential changes to mFIT may include adding, removing, combining, renaming, redefining, or dividing mFIT elements. I developed a set of revisions for mFIT to address the main issues identified in study 1. Study 2 included a survey and individual interviews with older adult diabetics to identify the tailoring elements that support their diabetes self-management apps. I revised mFIT a second time based on this studies results. Study 3 consisted of a survey and individual interviews with mobile app developers to identify the tailoring elements developers perceive as facilitating diabetes self-management. Issues identified in the third study informed an additional set of mFIT revisions.

Research Sites

The Mastick Senior Center, located in Alameda, CA, served as a research site for this study. This publicly funded senior center provides programs and services for health, education, and recreation at no cost to over 150,000 older adult attendees per year. Alameda is an island city located in the San Francisco Bay Area, with a population of over 73,000 people, almost 10,000 of whom are over the age of 65. Almost half (49.2%) of the city's population are racial and ethnic minorities, of which 30.9% are Asian and 11% are Hispanic (United States Census Bureau, 2015). I selected this site because of the large number of older adults that frequent the center, and because the senior center provides a convenient, easily accessible place to recruit older adults. The senior center's letter of commitment is included as Appendix A.

Along with the Mastick Senior Center, I recruited older adults from Texas cities that included Austin, Corpus Christi, and San Angelo. Austin is located in Central Texas and includes 947,890 people, with an estimated 74,883 of whom are over 65 years old (United States Census Bureau, 2017). Corpus Christi is located in South Texas and includes 325,605 people, with an estimated 41,667 adults over 65. San Angelo is located West Texas and includes 100,119 people, with an estimated 14,317 adults over 65 (United States Census Bureau, 2017). I selected these sites because they hosted diabetes self-management classes for older adults through their local YMCA.

In addition to recruiting older adults, I recruited mobile app developers from Austin, Texas and the San Francisco Bay Area. I selected these areas because of their access to mobile app developers, and because the areas include large universities that educate and employ developers.

Participants

I used standard recruitment approaches to recruit older adult participants. These approaches consisted of recruiting older adult participants by posting flyers at local organizations such as senior centers, libraries, churches, and centers providing services to diabetics, such as dialysis centers or local diabetes organizations. Along with flyers, I used the snowball sampling technique, where I asked participants to recruit potential participants for future interviews. Inclusion criteria for older adults required that participants were at least 65 years old and diagnosed with diabetes. Before the study began, I provided older adult participants with a cover letter approved by the Institutional Review Board at The University of Texas at Austin.

Older adult participants

A total of eighteen older adults participated, with ages ranging from 65-87 (mean 72.89, SD = 6.09) between over the course of six months between June 2018 and November 2018. Table 8 below includes demographics and characteristics for these older adult participants.

Table 8: Older adult characteristics

Variable	*n*	*%*
Gender		
Female	12	67
Male	6	33
Highest level of education		
No formal education	1	5
Less than high school graduate	1	5

High school graduate/GED	4	22
Vocational training	2	11
Some college/associate’s degree	3	17
Bachelor’s degree	5	28
Master’s degree or other postgraduate training	2	11
Doctoral degree	0	0
Health		
Poor	1	5
Fair	4	22
Good	9	50
Very Good	3	17
Excellent	1	5
Hispanic/Latino		
Yes	8	44
No	10	56
Ethnic Group		
American Indian/Alaska Native	0	0
Asian	0	0
African-American/black	2	11
Multi-racial	2	11
Native Hawaiian/Pacific Islander	0	0
White/Caucasian	11	61
Other	3	17

English as first language		
Yes	15	83
No	3	17
Experience using apps		
Less than one year (< 1 year)	8	44
More than one year, less than one year (1-3 years)	3	17
More than three years, less than five years (3-5 years)	3	17
More than five years, less than ten years (5-10 years)	1	5
More than ten years (>10 years)	3	17

Along with these average demographics and characteristics measurements, information about individual profiles for each older adult participant appears in table 9 below. Note that a pseudonym appears for each participant to preserve their anonymity. I use these pseudonyms in the results section as well.

Table 9: Mobile app developer characteristics

Name	Age	Gender	Education	Health	Hispanic	Race	English	Experience
Jill	67	Female	High school	Poor	Yes	Other	Yes	1-3 years
Burt	69	Male	Some College	Good	Yes	Other	Yes	1-3 years
Rosa	73	Female	Some College	Fair	No	White	Yes	5-10 years
Roberta	65	Female	High school	Good	No	White	Yes	1-3 years
Paula	65	Female	Master's degree	Very good	No	White	Yes	5-10 years

Jack	82	Male	Vocational training	Fair	No	White	Yes	Never
Elle	80	Female	Less than high school	Good	Yes	Multi-racial	No	1-3 years
Kathy	72	Female	Vocational training	Good	No	Multi-racial	Yes	Never
Ramona	72	Female	High school	Very good	No	White	Yes	3-5 years
Nia	70	Female	Bachelor's degree	Good	No	White	Yes	Less than a year
Clyde	71	Male	Some College	Fair	Yes	Other	Yes	Never
Sandy	67	Female	High school	Good	Yes	White	No	Never
Katherine	87	Female	No formal education	Good	Yes	White	No	Never
Bob	73	Male	Bachelor's degree	Excellent	No	White	Yes	1-3 years
Filomena	77	Female	Master's degree	Good	Yes	White	Yes	Less than a year
Johnson	80	Male	Bachelor's degree	Fair	No	White	Yes	5-10 years
Carly	70	Female	High school	Very good	No	African-American	Yes	Less than a year

Mobile app developer participants

I recruited mobile app developers using the snowball sampling technique. I first used professional contacts to recruit an initial group of mobile application developers from the San Francisco Bay Area. After completing the survey questionnaire and individual interview, I asked these participants for assistance in recruiting other developers from the area. Additionally, I recruited developers using contact information for mobile app developers provided by the Apple App Store and Google Play Store. I focused on developers of diabetes apps, along with developers of apps related to the seven self-management behaviors identified by The American Association of Diabetes Educators (2018). These behaviors include healthy eating, physical activity, blood-glucose self-monitoring, medication management, problem solving, risk reduction, and healthy coping. Inclusion criteria for app developers required that participants have experience developing a mobile app for diabetes management, or experience developing an app. Before the study began, I provided these developer participants with a cover letter approved by the Institutional Review Board at The University of Texas at Austin.

A total of ten mobile app developers participated, with ages ranging from 30-67 (mean 46.7, SD 12.44) between over the course of six months between June 2018 and November 2018. Table 10 below includes demographics and characteristics for these participants.

Table 10: Mobile app developer characteristics

Variable	*n*	%
Gender		
Female	3	30
Male	7	70
Highest level of education		
Less than high school graduate	0	0
High school graduate/GED	0	0
Vocational training	0	0
Some college/associate's degree	1	10

Bachelor's degree (BA, BS)	3	30
Master's degree or other postgraduate training	2	20
Doctoral degree	4	40
Hispanic/Latino		
Yes	2	20
No	8	80
Ethnic Group		
American Indian/Alaska Native	0	0
Asian	1	10
African-American/black	0	0
Multi-racial	0	0
Native Hawaiian/Pacific Islander	0	0
White/Caucasian	7	70
Other	2	20
Experience developing apps		
Less than one year (< 1 year)	3	30
More than one year, less than one year (1-3 years)	3	30
More than three years, less than five years (3-5 years)	3	30
More than five years, less than ten years (5-10 years)	0	0
More than ten years (>10 years)	1	10

Along with these average demographics and characteristics measurements, information about individual profiles for each developer appears in table 11 below. Note that the name for each participant uses a pseudonym to preserve their anonymity. I also use these pseudonyms in the results section below.

Table 11: Individual profile of mobile application developers

Name	*Age*	*Gender*	*Education*	*Hispanic/ Latino*	*Race*	*Experience*
Isaac	52	Male	Master's	No	White	3-5 years
Maya	37	Female	Bachelor's	No	Asian	Less than 1 year
Harold	66	Male	Some College	No	White	More than 10 years
Cal	67	Male	Doctoral Degree	No	Other	3-5 years
Franklin	50	Male	Bachelor's	No	White	1-3 years
Irene	44	Female	Master's	No	Other	Less than 1 year
Simon	47	Male	Bachelor's	No	White	1-3 years
Mia	36	Female	Doctoral Degree	Yes	White	1-3 years
Alejandro	30	Male	Doctoral Degree	Yes	White	Less than 1 year
Ava	38	Female	Doctoral Degree	No	White	3-5 years

MEASURES

This dissertation study used the following measures:

Basic Demographics

This study collected basic demographic data from participants that includes their age, gender, health, race and ethnicity, education, income, and primary language. See Appendices H and I.

Prior Experience

This study assessed participant's prior experience with the Internet, using mobile devices, and using mHealth apps to self-manage a chronic condition through self-report measures asking how long participants engaged in each of these activities. See Appendices H and I.

MATERIALS

This study used an iPad tablet computer running iOS version 10.3.3 for the content analysis. I elected to use a tablet computer rather than a smartphone because the tablet's large touchscreen display made it easier to discern and interact with onscreen objects. Also, by using a larger screen I limited my opportunity to miss small onscreen objects during the content analysis. I downloaded apps for the content analysis from the Apple App store and installed these apps on the iPad before the content analysis began. Interviews with older adults and app developers were guided by predetermined interview questions, which sought to further explore participant responses to the open-ended survey questions. A list of interview questions for older adults appears in Appendix B while a list of interview questions for app developers appears in Appendix C.

PROCEDURE

This research included three studies:

Study 1: Content analysis

The first study invovled a content analysis of 20 diabetes self-management apps using mFIT. First, I systematically selected 20 apps. Next, I applied mFIT to code the type and dose of tailoring used by each of the 20 selected apps. Based on this coding, I calculated an unweighted, composite score for each app[20].

To select apps for this content analysis, I adapted the app selection process used by a study on mHealth-based self-management apps (Stoyanov et al., 2015). As part of this selection process, I:

1. Conducted a search of Apple iTunes using the search terms "diabetes + self-management"[21].
2. Created an exhaustive list of free diabetes self-management apps.
3. Analyzed and scored apps on content, target audience, and tailoring.
4. Selected the 20 apps with the highest score for the final sample.

This process produced a composite score for each app that ranged from 1 to 48, and I selected the 20 apps with the highest score for the sample. Evaluating apps' content, target audience, and tailoring level ensured the selected apps focused on diabetes self-management, targeted older adults, and included tailoring.

To score the app content, I evaluated the degree that apps focused on the seven key diabetes self-management behaviors as defined by the American Association of Diabetes Educators (2018). These included healthy eating, physical activity, blood-glucose self-

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[20] In this context, higher mFIT scores did not reflect an app's effectiveness or usefulness, because the impact of each tailoring element is unknown.

[21] I focused my search on diabetes, rather than chronic conditions generally, as a preliminary search for "chronic + condition + self-management" produced numerous apps lacking a focus on managing a chronic condition.

monitoring, medication management, problem solving, risk reduction, and healthy coping. Apps received one point for each self-management behavior an app addressed. This approach produced a score for content that ranged from 0-7, where apps addressing no self-management behaviors received a score of 0 and apps addressing all seven self-management behaviors received a score of 7.

To score target audience, I evaluated the apps' focus on older adults. For this evaluation, I used a 5-point scale with the following anchors: 1) minimal focus on older adults; 2) some focus on older adults; 3) equal focus between older adults and other users; 4) mostly focused on older adults; and 5) exclusively focused on older adults. This evaluation produced a target audience score that ranged from 1-5 for each app with 1 meaning apps focused less on older adults and 5 meaning the app was exclusively focused on older adults.

To score tailoring, I used the mFIT framework to evaluate and score tailoring type and dose. This iteration of the mFIT framework produced an unweighted, composite score ranging from 0-16. Finally, I calculated an unweighted, composite score based on the sum of scores from my evaluation of content, target audience, and tailoring. This composite score ranged from 1 to 48. I selected the 20 apps with the highest score for the content analysis.

Study 2: Individual interviews with older adults with diabetes

The second study consisted of a survey and individual interviews with older adult participants diagnosed with diabetes. First, I contacted participants by phone, mail, or email to introduce them to the study, answer their questions, and provide them with the cover letter approved by the Institutional Review Board (IRB) at The University of Texas at Austin. A copy of this letter appears in Appendix D below. Next, participants completed a two-part survey questionnaire, in person, via email, or over the phone. The first part collected basic demographic information, such as age, education, and experience using mobile devices. The second part included four open-ended questions on the mFIT framework.

After participants completed the survey questionnaire, I conducted a semi-structured individual interview by email or in person with each participant.[22] This interview explored participant responses to the open-ended survey questions in greater depth. After completing this study, I revised mFIT V1 using older adults' feedback.

Study 3: Individual interviews with mobile application developers

The third study also used a survey questionnaire and individual interviews, but with mobile application developers. First, I contacted the developers by email, phone, or in-person to introduce them to the study, answer their questions, and provide them with a cover letter approved by the Institutional Review Board at The University of Texas at Austin. This letter appears in Appendix D below. Next, participants completed a two-part survey questionnaire. The first part collected basic demographic information, such as age, education, and experience using mobile devices. The second part included four open-ended questions on the mFIT framework.

After the developers completed and returned the survey questionnaire, I interviewed each participant by phone or email. These interviews explored participant responses to the open-ended survey questions in greater depth. After completing this study, I revised mFIT based on participants' feedback.

Data analysis

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[22] I elected to conduct interviews via email, in-person, or by phone to make the study accessible to disabled participants.

I used inductive thematic analysis to analyze the data from the semi-structured in-depth individual interviews with older adults and developers. Thematic analysis is "a method for identifying, analyzing, and reporting themes with data" (Braun & Clarke, 2006, p. 79). Specifically, inductive thematic analysis provides a bottom-up, data-driven approach to thematic analysis that does not depend on extant coding schemes or theoretical concepts (Braun & Clarke, 2006). I chose an inductive approach, rather than a deductive approach, to facilitate a data-driven analysis independent of the mFIT framework. This analysis involved six phases that I completed separately for the older adult diabetics and the mobile app developers.

Prior to the analysis, I developed separate qualitative data sets for the older adult diabetics and the mobile app developers. These data sets consisted of the qualitative data I collected with the open-ended questions in the survey questionnaires and individual interviews. First, I created a single document that collated participant responses to the open-ended survey questions. This document used participant pseudonyms so I could track their responses throughout the data set. Next, I added data from the individual interviews to this document. This interview data comprised of interview responses and my contemporaneous notes on the interview. Additionally, this interview data included notes on my initial impressions and reflections following each interview. This process produced a separate data set for the older adult diabetics and mobile app developers that served as the basis for my analysis. Following Braun and Clarke's guidelines (2006), I carried out the following phases:

Phase 1: I familiarized myself with the data set. This process involved reading through the data set several times while taking notes for potential codes and initial patterns I identified in the data. For instance, I noted that a number of the older adult participants emphasized issues with the visual characteristics of their diabetes self-management apps.

Phase 2: I developed an initial set of codes I identified in the data. For instance, I developed a code for when older adult participants described apps using color to communicate information. Consistent with an inductive approach to thematic analysis, I developed these codes independent of the mFIT framework, and did not use the survey or interview questions for guidance. Next, I coded the remaining data with the initial codes. For each of these initial codes I collated the data extracts that shared codes, such that the data set was now organized by the initial codes.

Phase 3: I developed themes from the codes developed in the second phase. In contrast with codes, a theme "captures something important about the data in relation to the research question, and represents some level of patterned response or meaning within a data set" (Braun & Clarke, 2006, p. 82). In addition to these themes, I developed sub-themes and a thematic map to visualize the relationship between the sub-themes and themes.

Phase 4: I reviewed the themes developed in the third phase. During this review process, I first examined the data extracts for each theme to ensure the coherency of the themes developed in the third phase. Once I confirmed these data extracts produced a coherent pattern for each theme, I expanded this review process to the thematic map. This broader review ensured the thematic map truly represented the key aspects of the data set.

Phase 5: I confirmed that the thematic map accurately described the data set. In the fifth phase I further refined the themes I reviewed in the fourth phase. This process involved reviewing the data extracts for each theme an additional time, examining the narrative the theme conveys, and considering the way each theme relates to the broader narrative expressed by the data set.

Phase 6: I wrote the report for this thematic analysis, which appears in the results section below. I performed this portion of the analysis using Atlas.ti, a software tool used for analyzing qualitative data.

I complemented this thematic analysis with quantitative data sets I developed using participant responses to the multiple choice survey items from the survey questionnaire. As with the qualitative data, I developed separate data sets for the quantitative data collected for older adult diabetics and mobile app developers. I developed these quantitative data sets by entering participant responses into SPSS. During the data entry, I reviewed the data to verify it contained missing values and accuracy. Next, I used descriptive statistics to provide a statistical profile of participants. For categorical data I reported both frequency and percentage in the results section in Chapter 5. Likewise, for continuous data I report mean and standard deviation in the results section below.

Chapter 5: Results

This chapter presents the results from the content analysis of self-management apps, along with the surveys and interviews with older adults and developers. First, I present the content analysis results, where I evaluated a set of diabetes self-management apps with mFIT Version 1 ("mFIT V1"). This evaluation process identified benefits for mFIT V1, and main issues with evaluating apps using mFIT. Based on these issues I developed a set of seven framework revisions, which included redefining, revising, and consolidating elements. This revision process produced mFIT Version 2 ("mFIT V2") with seven elements.

Second, I present results from the survey and individual interviews with older adult diabetics. This process identified tailoring elements from mFIT V2 that older adult diabetics felt facilitated their diabetes self-management. Also, I identified three benefits of the mFIT V2, and identified four major categories of issues with the framework, along with sub-categories of issues. I developed a set of four revisions to mFIT V2 to address these issues. This revision process created mFIT Version 3 ("mFIT V3") a revised, more parsimonious iteration of the framework with six elements.

Third, I present results from the survey and individual interviews with mobile application developers. I first identified the tailoring elements from mFIT V3 that developers perceived as facilitating older adults diabetes self-management. Also, I identified several benefits of the mFIT V3 elements, and three main issues with the mFIT V3 elements, by interviewing developers. Next, I made several revisions to mFIT V3 to address these main issues. This process produced mFIT Version 4 ("mFIT V4"), which includes six tailoring elements. mFIT V4 is the final mFIT framework generated in this dissertation research.

STUDY 1: FINDINGS FROM CONTENT ANALYSIS OF APPS

The content analysis included three parts. First, I selected apps for the content analysis using the selection criteria detailed above. This process produced a set of 20 tailored diabetes self-management apps. Second, I conducted a content analysis of the selected apps using mFIT V1. This content analysis identified seven key issues with mFIT V1 that required revision. Additionally, in this part I present the benefits of mFIT V1 identified during the content analysis. mFIT V2, the product of this revision process, is then presented.

App selection

I conducted four rounds of screening with a selection of 100 apps during March 2017 to identify apps for the content analysis. To begin, on March 9, 2017, I conducted a search of the Apple App Store for "diabetes self-management." This search produced an initial set of 100 apps, the maximum number of apps provided by the display. A complete list of these apps appears in Appendix E below. To identify free apps focused on diabetes self-management, I conducted four rounds of screening prior to the start of the content analysis. During this screening, I evaluated apps to ensure they carried no charge and focused on diabetes self-management. Additionally, I removed apps that lacked interactive features, such as apps presenting content from a magazine or book. I removed these apps because of this dissertation's focus on tailoring, which depends on interaction. This screening process ensured apps selected for the content analysis focus on diabetes self-management.

Round 1: Apps charging for download or self-management features

First, I screened the initial list of apps ($n = 100$) to confirm they carried no fee for download or self-management features. I excluded paid apps because this project lacked sufficient funding to purchase paid apps for screening. Additionally, I chose to screen the apps for charging, rather than rely on the iTunes App Store, because apps listed in the store as free may sometimes include features that carry a charge. Similarly, I excluded apps charging for self-management features. For instance, I excluded the Low-Glycal Diet app because it charges for tailored self-management information. However, I did include apps with in-app purchases, so long as they did not charge for self-management features. For instance, I included apps that charged to block ads, such as the PredictBGL app. Applying these criteria, I removed 27 apps for carrying fees, leaving 73 apps.

Round 2: No diabetes focus

Second, I removed apps with no focus on diabetes (n = 12). For instance, I removed fitness apps, such as Fat Lady Fitness, 20 Minute Ab Workouts app, Female Fitness Workouts, 7 Minute Chi, and the Workouts Free app. Similarly, I excluded apps that focused only on general or preventative health issues. For instance, the GenieMD app provides a tool for organizing health information related to allergies, medications, immunizations, medical records, and exercise, but does not specifically focus on diabetes. Applying the criteria to remove apps with no diabetes focus, I removed 12 apps, leaving 61 apps.

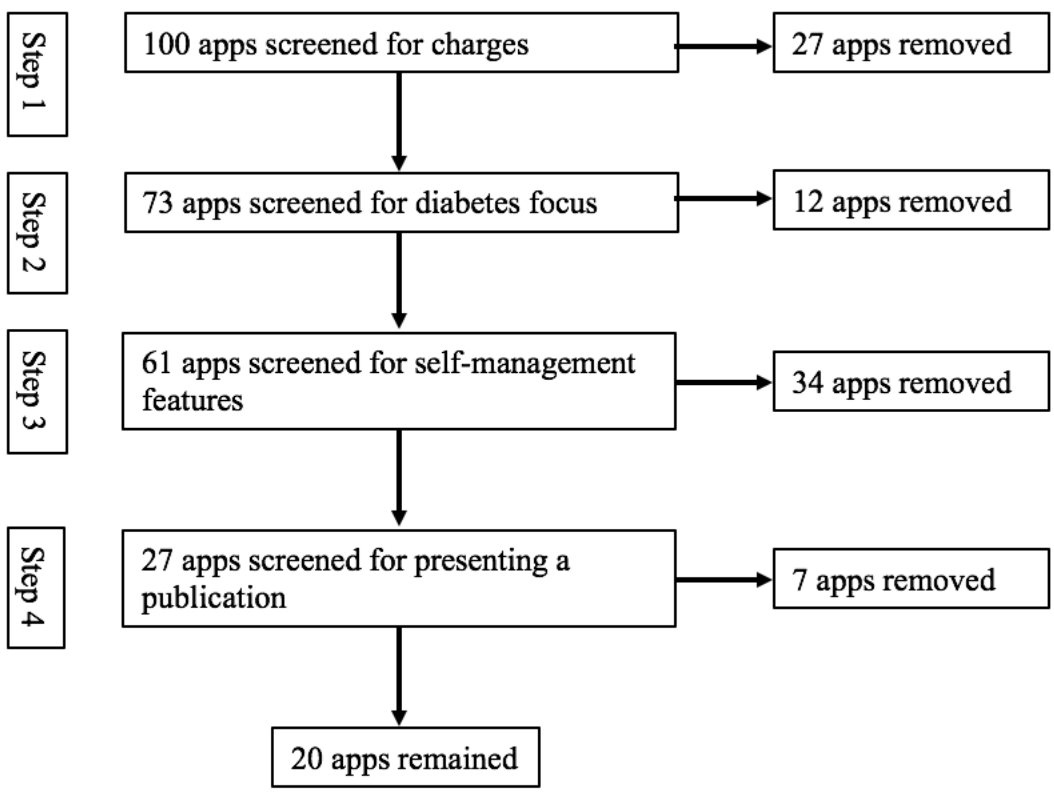
Round 3: No self-management focus

Third, I removed apps lacking self-management features (n = 34). To determine whether an app included self-management features, I used the definitions and examples of self-management activities that appear in Appendix F below. For instance, I removed the Diabetes Emoticon app, which enables users to send diabetes related emoticons via text message. While a potentially useful diabetes communication tool, this app included no self-management features. Likewise, the Pregnant with Diabetes app included information about pregnancy topics but included no self-management features. After removing these 34 apps for not including self-management features, 27 apps remained.

Round 4: No interactive features

Fourth, I removed apps that only present content from mobile publications, such as magazines or cookbooks (*n* = 7). This category includes mobile magazines focused on diabetes, such as Diabetic Living Magazine, Diabetes Digest, Diabetes Lifelines, and the Well Being Journal. Additionally, this category includes mobile cookbooks, such as the Diabetes Cookbook, Diabetes App Recipe, and the Recipes for Diabetes apps. After removing these 7 apps, 20 apps remained. Figure 4 below summarizes this selection process

Figure 4: App screening process



This selection process produced a total of 20 diabetes self-management apps that appear in appendix G below, which includes information on the app's developer, and the date of the app's most recent update.

Content Analysis

Next, I conducted a content analysis of the 20 apps. To conduct this analysis, I downloaded and installed each of the 20 apps and used their self-management features over the course of a month. During this period, I recorded self-management behavior several times each day with the 20 apps, varying the times I recorded the behavior each day at random. I varied the time of day I recorded behaviors to increase the opportunity for the app to provide tailored content. Each time an app delivered a tailored message, I recorded both the timing, content, and modality used to provide the message.

First, I evaluated which self-management behaviors the apps address. The number of self-management behaviors the apps addressed ranged between 0 and 5 (M = 3.00, SD = 1.63). The most common behaviors supported by the apps included blood-glucose self-management (n = 14), followed by medication management (n = 12), and healthy eating (n = 11). Table 12 below includes the frequencies for each behavior. Notably, no app supported either healthy coping or risk reduction, and no app focused on a specific population, such as older adults.

Table 12: Self-management behaviors identified among apps

Self-management behavior	*n(%)*
Blood-glucose self-management	14(70)
Medication management	12(60)
Healthy eating	11(55)
Physical activity	9(45)

Problem solving	7(35)
Risk reduction	0
Healthy coping	0

Next, I evaluated and quantified each app's tailoring level using mFIT V1, with scores ranging from 0-7 (M = 2.88, SD = 1.71). The most common tailoring approach included descriptive feedback (n = 13), comparative feedback (n = 9), and the raising the expectation of customization type of personalization (n = 9). No app tailored dose elements such as amount, frequency, sequence, or delivery system. Additionally, no app qualified as using theory-based content matching elements. Table 13 below includes the frequencies for each self-management behavior.

Table 13: Tailoring elements identified among apps.

Tailoring element	*n(%)*
Descriptive feedback	13(65)
Comparative feedback	9(45)
Raising the expectation of customization	9(45)
Evaluative feedback	7(35)
Degree of control	3(15)
Identification	2(10)
Framing	1(5)
Event-triggered	1(5)

mFIT V1 Benefits

Along with the content analysis results, I identified three benefits of mFIT V1 during the content analysis. First, the content analysis confirmed the framework's ability to quantify the type and dose of tailoring provided by diabetes self-management apps. This quantification can enable researchers to better understand the way different dose elements and types impact self-management. For instance, the GlucoseGuide app received a score of 7, which reflects a higher level of tailoring than the Diabetes Aid app, which received a score of 1. While it remains unknown whether higher tailoring levels improve outcomes, mFIT V1 provides a key contribution for understanding this relationship.

Second, mFIT V1 provided a comprehensive account of tailoring elements. The comprehensiveness of this framework contrasts with prior categorizations of tailoring elements, such as the proposed reporting standards (Harrington & Noar, 2012), which did not account for these potentially impactful elements. For instance, the message effects model did not include the feedback type of tailoring, while the proposed reporting standards identified four types of feedback (Krebs et al., 2010; Lustria et al., 2013). A comprehensive evaluation of tailoring elements that uses these elements can help researchers understand the influence of key, impactful tailoring elements. For instance, the D-life app included degree of control, a tailoring element developed in chapter 3 to account for the control apps give users over when they receive information. Accounting for these previously unidentified elements can help identify the elements that support tailoring.

Third, I designed mFIT V1 specifically for older adults using tailored diabetes self-management apps, in contrast with prior approaches to evaluating tailoring. Prior tailoring models, which include the message effects model and the proposed reporting standards, did not focus on a specific condition or population (Harrington & Noar, 2012; Noar et al., 2009). Alternately, studies investigating tailoring's mechanisms focused on conditions other than diabetes, such as a study investigating tailored interventions to promote sexually transmitted disease testing for older adults (Lustria et al., 2016). Developing a framework specific to diabetes can provide potential benefits given that diabetes self-management involves up to seven complex self-management behaviors. If effective in this context, the framework can be adapted to additional contexts, such as tailoring self-management of hypertension.

Main issues identified and subsequent revisions

This section reports the five main issues I identified with mFIT V1 during the content analysis. I describe each main issue below, and for each main issue I present the subsequent revisions to mFIT V1 that address the issue. This process produced a set of six revisions that reduced the number of tailoring elements from 16 to 7. Additionally, this process updated the definitions and examples for the remaining elements. This process produced a revised, more parsimonious mFIT V2.

Main Issue 1: Distinguishing between content matching and framing

First, I identified a main issue distinguishing between the decisional balance construct from the transtheoretical model, the perceived benefits and barriers constructs from the health belief model[23], and the framing tailoring type. The transtheoretical model asserts that as individuals progress through the stages of change, they increasingly value the pros of a health behavior over the cons of not engaging in a behavior. In practice, distinguishing when apps use decisional balance, perceived benefits and barriers, or framing proved difficult due to these elements' similarities. For instance, the Glucoguide app provided a tailored message stating, "fiber helps with your blood sugar, cholesterol, weight, and blood pressure." Under mFIT V1

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[23] Both decisional balance and the perceived benefits and barriers constructs are used to for content matching.

this statement could alternately be coded as using decisional balance, perceived benefits, or framing. In this instance, I used my discretion to code the message for perceived benefits rather than decisional balance or framing.

To address this main issue, I revised the definition of theory-based content matching to give the evaluator discretion on choosing the theory to code. As before, theory-based content matching requires that an app tailor each construct from a theory. However, this new approach clarifies that evaluators should use their discretion to decide whether to code a message as tailoring for decisional balance, perceived barriers and benefits, or framing. For instance, a message stating “physical activity such as walking can help you stabilize your blood glucose and control your weight” can qualify as either decisional balance, perceived benefits and barriers, or framing. As a result, I revised the app evaluation form to clarify that evaluators can indicate which theory they coded for content matching.

Main Issue 2: Distinguishing between descriptive and comparative feedback

Second, my content analysis identified a main issue distinguishing between descriptive and comparative feedback. As defined, descriptive feedback presents objective data on an individual’s self-management, while comparative feedback compares participant data with others or themselves. The content analysis found that no apps compared participant data with their peers, but apps did compare users to themselves. Problematically, as defined, apps that provide comparative feedback necessarily also provide descriptive feedback. This main issue arose because as defined, descriptive feedback serves as the basis for comparison with comparative feedback. Consequently, apps coded for comparative feedback all received codes for descriptive feedback, reflecting the practical issue with these two feedback elements.

To address this main issue, I revised the comparative and descriptive feedback elements to clarify their relationship. In this revised approach I redefined comparative feedback to include descriptive feedback. Under this approach, comparative feedback still compares participant's data to themselves, while descriptive feedback presents objective data on an individual's self-management. For instance, to code using this revised approach, apps that provide descriptive feedback receive 1 point, while apps that provide comparative feedback receive 2 points. This revised approach can resolve the issue of distinguishing between descriptive and comparative feedback.

Main Issue 3: Distinguishing between comparative and evaluative feedback

Third, the content analysis identified a main issue distinguishing between the comparative and evaluative feedback elements. As defined, evaluative feedback judges or interprets participant data. Problematically, the definition's breadth generates difficulty distinguishing between evaluative and comparative feedback. For instance, the EZBDS app states "you've eaten similar meals once in the past three months" regarding a hamburger. This statement qualifies as evaluative feedback because it makes a judgment about the participant's diet. However, the statement also qualifies as comparative feedback by comparing the participant's diet over three months. Likewise, the statement "you eat fewer fruits than your peers", also provided by the EZBDS app, qualifies as both evaluative and comparative feedback. This overlap suggests these elements lack sufficient distinctiveness to justify their inclusion in the framework.

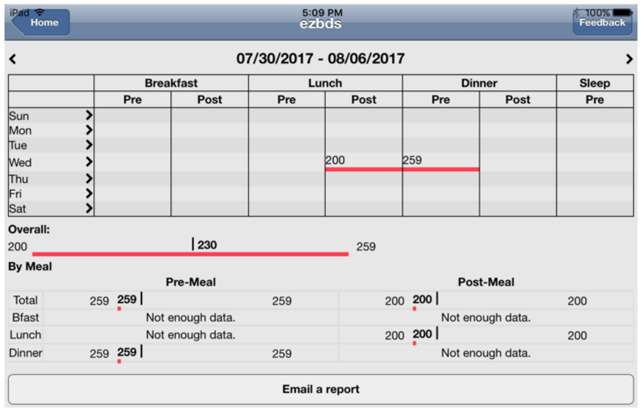
To address this main issue, I redefined the descriptive and evaluative feedback elements. In this new approach, descriptive feedback reports raw data back to a participant, while evaluative feedback interprets participant data before giving it to participants. Notably, these revisions make the definitions mutually exclusive. Further, examples can clarify the distinction between these elements. For instance, an app that reports glucose readings back to participants provides descriptive feedback, so long as that app does not manipulate that data. Alternately, a tailored message reading "you've eaten similar meals once in the past three months" interprets participant data and qualifies as evaluative feedback. Similarly, a message reading "you eat fewer fruits than your peers" qualifies as evaluative feedback because the app interprets the data by comparing the participants' data to their peers' data.

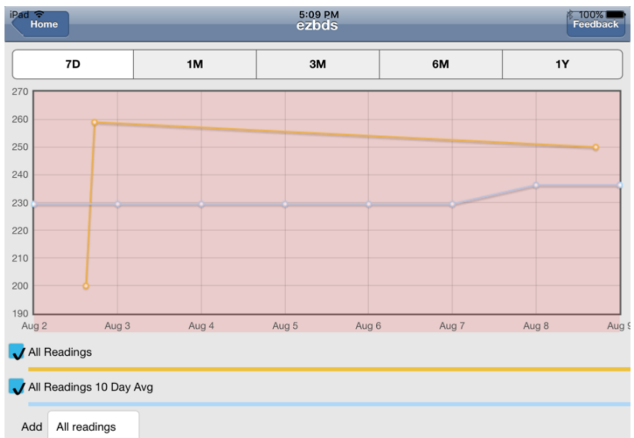
Figure 5 below presents examples of descriptive and evaluative feedback. Examples of evaluative feedback include the statement "you've eaten similar meals in the past month, but this meal is not helpful to your weight goals". This statement makes an evaluation of the participant's diet over the past month and evaluates this data in the context of the participant's weight goals. In contrast, the descriptive feedback example provided by the EZBDS app reports data back to the participant without evaluating the data. (As an example, this data appears in the form of a food diary for the week of July 30, 2017.) Similarly, descriptive feedback regarding blood glucose levels appears for the same period in a figure below.

Figure 5: Descriptive and evaluative feedback

Feedback type	*Examples*
Evaluative feedback	"You've eaten similar meals in the past month, but this meal is not helpful for your weight goals"

Descriptive feedback





Along with redefining descriptive and evaluative feedback, I removed the objectivity requirement for descriptive feedback. I removed this requirement because some apps enable users to track their subjective impressions on their mood. For instance, the DiabetesConnect app helps people to track subjective experiences, such as feeling vulnerable, confident, helpless, tired, weak, nervous, stressed, dizzy, confused, or mood swings. Imposing an objectivity requirement could exclude such data without justification, and no benefit to an objectivity requirement emerged during the content analysis.

Main Issue 4: Contextualization element too broad

No app tailored the contextualization element, in part due to the element's breadth. As defined, contextualization situates "messages in a context that is meaningful to individuals"

(Harrington & Noar, 2012, p. 336). Problematically, this definition's breadth offers little indication of which messages qualify as contextualized. An example of contextualization included with the definition suggests integrating cultural images into the messages qualifies as contextualization (Harrington & Noar, 2012, p. 336). This example suggests messages integrating a participant's culture as the basis for tailoring. However, this example provides no specific example of a contextualized content that includes cultural images.

The 'Diabetes in Check' app can exemplify contextualized content by using the phrase "get the 411." This phrase describes where users can find information, and may confuse non-American English speakers, such as someone speaking Ulster English. While this example demonstrates the way apps use culture, this app only uses American English, with no feature for changing dialect. Similarly, this app used pounds to measure weight, the standard in the United States, while other apps, such as 'DiabetesConnect', used the metric system. Notably, neither app tailored for measurement system or gave users the ability to change measurement system. Such cultural differences could confuse or create difficulties for individuals unfamiliar with a measurement system.

To address this main issue, I redefined contextualization to include more specific examples of contextualization. In this new approach, I define contextualization as tailoring that situates messages in a meaningful cultural context for individuals. This definition differs from the original definition by explicitly focusing on culture. Additionally, this definition aligns with the cultural tailoring literature, which investigates tailoring for factors excluded from content matching, such as an individual's name, age, or language. No consensus definition applies to cultural tailoring, with definitions that describe cultural tailoring as "contextual influences… that may influence the way individuals understand and process health information" (Kreuter et al.,

2005) or simply “tailoring on cultural variables” (Davis et al., 2011). “Get the 411” can provide an example of contextualization under the revised contextualization definition. This revised example can help evaluators identify contextualization among apps.

Main Issue 5: No information on the algorithms that tailor dose

My content analysis identified a main issue assessing dose that occurred because the selected apps masked the algorithms used to tailor that information. For instance, the GlucoGuide app sends tailored messages at different frequencies, but whether it tailors frequency remains unclear. This ambiguity exists because evaluators must track when an app delivers messages to identify changes in frequency. These changes in frequency would provide evidence that the app tailors frequency. For instance, the GlucoGuide app may provide messages at different frequencies because that app targets information, or because the app sends information at random. Notably, this main issue did not occur for event-triggered tailored information, as an evaluator can directly observe the event related to the message.

To address this main issue, I consolidated the amount, frequency, sequence, and delivery system elements into a single element called dose. Given that tailoring algorithms are inaccessible to evaluators, determining if an app tailored these elements remains difficult, and requires evaluators to record when apps deliver tailored information. Consolidating these elements simplifies the process of determining whether an app tailors the dose by limiting the number of elements evaluators must assess. For instance, if an evaluator identifies an app that tailors for frequency, they do not need to assess the app for additional elements, such as amount or sequence. This revision addresses this practical issue with dose, making it easier to evaluate tailoring using mFIT.

This part identified five main issues with theory-based content matching, feedback, personalization, framing, and dose that emerged during the content analysis. For each main issue, I present a revision that addresses that main issue. First, I identified a main issue distinguishing between content matching and framing. To address this main issue, I redefined contextualization, and consolidated the identification and raising the expectation of customization elements into a single element called personalization. Second, I identified a main issue distinguishing between descriptive and comparative feedback. To address this main issue, I revised the scoring for descriptive and comparative feedback. Third, I identified a main issue distinguishing between comparative and evaluative feedback. To address this main issue, I redefined the evaluative and descriptive feedback elements. Fourth, the contextualization element used a broad definition that made it difficult to code. To address this main issue, I redefined the contextualization element. Fifth, a main issue emerged in evaluating dose because the apps provided no information on the algorithms that tailor dose. To address this main issue, I consolidated the amount, frequency, sequence, and delivery system elements into a single element called dose. Table 14 below summarizes these five main issues and the subsequent revisions.

Table 14: Five Main Issues and Subsequent Set of mFIT revisions

Main Issue	*Description*	*Revisions*
Main Issue 1	• Difficult to distinguish content matching from framing.	• Redefined contextualization. • Consolidated the identification and raising the expectation of customization elements into a single element called personalization.
Main Issue 2	• Difficult to distinguish between descriptive and comparative feedback.	• Revised the scoring for the comparative and descriptive feedback elements.

Main Issue 3	• Difficult to distinguish between comparative and evaluative feedback.	• Redefined evaluative and descriptive feedback.
Main Issue 4	• Contextualization element too broad.	• Redefined the contextualization element.
Main Issue 5	• No information on the algorithms that tailor dose	• Consolidated the amount, frequency, sequence, and delivery system elements into a single element called dose.

Revised mFIT framework

Using the revisions described above, I revised mFIT V1 and developed mFIT V2. In this section, I explain the key components of mFIT V2 and how they can be used to evaluate and quantify tailoring for chronic condition self-management apps. mFIT V2 includes seven elements, five of which address tailoring type (personalization; contextualization; descriptive feedback; evaluative feedback; content matching) and two of which address dose (dose; event-triggered information). Table 15 below presents each tailoring type, along with revised definitions and examples where applicable. These definitions and examples can function to code and score different tailoring types and dose, and each type receives an unweighted score of one point. As a result, tailoring type under mFIT V2 can range from 0-5. Additionally, mFIT V2 no longer uses the terminology sub-type to discuss tailoring type. This revision streamlines and simplifies mFIT V1 by reducing the number of distinctions drawn between different elements. This new approach eliminated the need to include a separate scoring process for theory-based content matching, as required for mFIT V1.

Table 15: mFIT V2 tailoring types

Type of tailoring	*Definition*	*Example*

Personalization	A message that indicates a message is designed specifically for an individual.	"We developed this message just for you, based on your dietary preferences and needs."
Contextualization	Situate messages in a meaningful cultural context for an individual.	Tailoring the dialect used by an app based on user characteristics.
Descriptive feedback	Feedback that reports raw data back to a participant.	A table listing each glucose reading a participant took during the course of a month.
Evaluative feedback	Feedback that interprets participant data prior to providing it to a participant.	"You have eaten similar meals once in the past three months"
Content-matching	Messages tailored for constructs from health behavior change theories.	"Your risk of developing co-morbidities will increase if you do not manage your diabetes."

mFIT V2 assesses two elements of dose with the non-event triggered dose element and the event-triggered dose element. Definitions and examples for these elements appear in table 16 below. As with tailoring type, evaluators can apply these definitions and examples to code and score the elements of dose apps tailor. These scores remain unweighted given the lack of research on the impact of each element. In conjunction, the sum of these elements generates a score ranging from 0-2.

Table 16: Dose for mFIT V2

Type of tailoring	*Definition*	*Example*
Non-event triggered dose	Tailoring the amount, frequency, sequence of information provided, along with the delivery system used to provide tailored information.	An app sends a user a brief tailored message once per day because the user ignores more frequent, longer messages.
Event-triggered dose	The app tailors the information provided when an event occurs.	An app sends a user a warning after they report

		an especially high glucose level.

After developing mFIT V2, I evaluated the framework using qualitative data I gathered from older adults with diabetes. I report on the results of this evaluation in the next part below.

STUDY 2: TAILORING ELEMENTS OLDER ADULTS PERCEIVE AS FACILITATING DIABETES SELF-MANAGEMENT AND REVISIONS

This section identifies the tailoring elements older adults with diabetes perceived as key to facilitating diabetes self-management. First, I describe the pilot test of the survey and individual interviews I conducted with the two groups of participants, older adults with diabetes, along with mobile app developers. Based on their suggestions, I revised the survey questionnaire and individual interview questions. Second, I present the mFIT V2 tailoring elements the older adults perceived as facilitating diabetes self-management. I present the themes I identified during the thematic analysis, which includes older adults' perceptions on three benefits for mFIT V2. Third, I present a set of issues with the mFIT framework I identified through a thematic analysis of the survey and interview data. Fourth, I developed a set of revisions to mFIT V2 to address these issues. Fifth, I present the mFIT V3 framework that incorporates the older adult diabetics' feedback. Taken together, this process generated mFIT V3, which includes seven tailoring elements.

Pilot test of survey questionnaires

Before using the survey questionnaires, I conducted two separate pilot tests of the instruments with older adults and app developers. The first pilot test recruited two older adult participants using personal contacts and the snowballing technique. After confirming their participation, these participants received a copy of the cover letter approved by the Institutional

Review Board at the University of Texas at Austin. Participants then received instructions to complete the questionnaire and provide feedback on any unclear or confusing aspects of the survey. Both participants completed the survey and provided feedback focused on clarifying the questionnaire's language. For instance, one participant suggested using the term 'mobile application' instead of 'app'. The participants felt using mobile application would "remind people of the word's meaning." In effect, by using the term mobile application, the survey questionnaire provided greater clarity for older adults unfamiliar with the abbreviation. Based on this feedback, I revised the questionnaire, which appears in Appendix I. Additionally, I translated the survey into Spanish, then asked several native Spanish speakers to confirm the translation. The Spanish language version of this survey appears in Appendix J below, along with a Spanish-language copy of the cover letter approved by the Institutional Review Board (Appendix K).

Using the same process, I conducted a second pilot test of the survey questionnaire developed for app developers. To conduct this test, I recruited two app developers through professional contacts using the snowballing method. After confirming their participation, I provided participants with a cover letter approved by the Institutional Review Board at the University of Texas at Austin, along with instructions to complete the questionnaire and provide feedback on any aspects of the survey that they perceived as confusing or unclear. These exchanges occurred via email and a copy of this introductory email appears in Appendix I below. Both participants completed the surveys and provided feedback.

The participants' primary feedback was to simplify and shorten the survey. For instance, one participant suggested "simplifying the wording on question 2 of part 2" in reference to the question that read "What edits would you make to the framework? This could include adding, removing, combining, renaming, redefining or dividing elements. Again, please explain the reasoning for your suggested change." Likewise, the other participant said "I started to lose extreme interest in doing this survey in section 2 when the survey started going over tailoring framework… especially when presented with a lot of data/reading for questions." This quote demonstrated a need to simplify the second part of the questionnaire.

In response to this feedback, I simplified the language and shortened the length of the survey questionnaire. For instance, I revised the second open-ended question to ask "which tailoring types do you believe could best support or facilitate users managing a chronic condition?" Similarly, I shortened the introduction to limit distractions and better describe tailoring. Also, I simplified the definitions and examples in the framework that appear in the questionnaire. For instance, the example of feedback in the initial draft stated, "a table listing out each glucose reading a participant took during a month." I revised this example to state, "you weigh 175 pounds." This short, revised example simplifies the framework and reduces the attentional demands placed on readers. A copy of this revised questionnaire appears in appendix J below.

Perceptions of mFIT V2 elements that facilitate diabetes self-management

Following the pilot study, I conducted my survey questionnaire and individual interviews with older adults. Among older adult participants, $n = 13$ indicated they used diabetes self-management apps to manage their diabetes. The tailoring elements participants perceived as supporting diabetes self-management included descriptive feedback ($n = 8$), personalization ($n = 5$), content-matching ($n = 5$), and non-event-triggered dose ($n = 5$), followed by contextualization ($n = 4$), then event-triggered dose ($n = 3$), and evaluative feedback ($n = 3$). Three participants found all of the elements key to facilitating their diabetes self-management. Absent these participants, no participant recognized event-triggered dose or evaluative feedback as supporting diabetes self-management during the survey questionnaires or individual interviews. Table 17 summarizes these results appears below.

Table 17: Tailoring elements perceived as facilitating diabetes self-management

Tailoring Type	*N(%)*
Descriptive feedback	8(44)
Personalization	5(28)
Content-matching	5(28)
Non-event-triggered dose	5(28)
Contextualization	4(22)
Event-triggered dose	3(17)
Evaluative feedback	3(17)

Participants used a selection of nine different apps listed in Table 18 below. The most popular apps used by participants included Diabetes Buddy (n = 3) and mySugr (n = 2), while one participant each used the remaining seven apps.

Table 18: Diabetes self-management apps used by participants

App Name	*Number of participants using the app*	*Developer*
Diabetes Buddy	3	mySugr GmbH
mySugr	2	Not available
Diabetes Pilot	1	Digital Altitudes, LLC
Diabetes Companion	1	Not available

Track 3	1	Coheso, Inc.
Accu-Chek Connect	1	Roche Diagnostics Operations, Inc.
BG Monitor	1	Not available
Dexcom	1	DexCom, Inc.
Glucose Buddy	1	Tom Xu

Next, I used thematic analysis to identify major themes in the qualitative data from the survey questionnaire and individual interviews. Major themes included three benefits for mFIT V2. These benefits included the participant perception that content-matching and contextualization motivated them to better self-manage their diabetes, participant perception that descriptive feedback provided a benefit by addressing their information needs, and participants perceived dose as benefiting them through providing just-in-time reminders to perform self-management behaviors. Likewise, my thematic analysis identified themes that included the main issues and their corresponding sub-issues. These main issue themes include the participant perception that presentation of tailored information makes it difficult to understand and use, distrust of tailored information, lack of cultural context for diet and physical activity made tracking for self-management difficult, and barriers to using tailored apps for diabetes self-management.

mFIT V2 Benefits

I identified three benefits for the mFIT V2 elements from the qualitative data. First, several participants perceived that content-matching and contextualization motivated them to better self-manage their diabetes. In particular, these participants felt the content-matching element motivated their performance of self-management behaviors, such as improving diet. For example, Bob, a retired teacher in Corpus Christi, perceived content-matching as beneficial because it provided "encouragement to help me get healthy." Similarly, Filomena, an older resident of Austin with a long history of diabetes, felt "content-matching helped push me with watching everything you eat and eating three healthy meals a day instead of two and junk food in between." Along with content-matching, Filomena's husband Burt, who also suffers from diabetes, felt that the contextualization element supported their self-management "because it provides encouragement." When asked to elaborate on the meaning of contextualization, Burt stated "culture is what's important to me and it keeps me in place." This comment references the function of contextualization as a tailoring type that situates messages in a meaningful cultural context.

Second, participants felt that descriptive feedback provided a benefit by addressing their information needs. For instance, Nia felt that descriptive feedback gave her key "information on my exercising, [and] walking. After walking my diabetes test results are lower." Likewise, Elle, a lady with experience using the apps for self-management, stated that with descriptive feedback "I get all the information" while Paula "like[d] having all the information about my body." Similarly, Nia liked that descriptive feedback "will give me information on weight." These statements show participants felt descriptive feedback provided a benefit for meeting their information needs. Further, these perceptions of descriptive feedback may explain why more participants identified descriptive feedback as facilitating diabetes self-management in comparison to the other elements.

Third, participants perceived dose as benefiting them through providing just-in-time reminders to perform self-management behaviors. In particular, participants thought dose supported them in taking their medication on schedule. For example, Johnson, a retired technology engineer, stated,

> I like alarms that remind me to take my med[ications]. I forget to take my pill and it causes me all sorts of issues because I don't know what to do. The alarm reminds me so I don't forget if I took my pill or not.

In a similar statement, Filomena stated that dose facilitated self-management because it "give[s] me an idea on when to take medication." Likewise, Burt said dose benefitted him "because adapting dose helps with [using the app] to manage when to take meds for my diabetes." Taken together, these statements evidence that participants perceived dose benefitted them by providing medication reminders.

Main Issues Identified

Along with participants' perceptions about the benefits of the mFIT V2 elements, my thematic analysis identified four main issues with tailored information. These major issues include the presentation of tailored information making it difficult for older adults to understand and use, a distrust of tailored information, a lack of cultural context, and barriers to using tailored apps among older adults that do not use app for self-management. Each category of issues includes subcategories I describe below.

Main Issue 1: The way apps present tailored information can make it difficult to understand and use

Participants perceived the way apps presented tailored information as problematic, making tailored information difficult to understand and use for self-management. mFIT V2 only describes the content of tailored information. Problematically, this approach overlooks the influence of the way apps present tailored information to users. This issue arose in four contexts, which include matching the mode used to present tailored information to user characteristics and preferences, the use of color to convey tailored information's meaning, difficulty perceiving onscreen information, and the perception that apps that pushed information were intrusive.

First, participants wanted the modality[24] used to present information to match user characteristics and preferences. Several participants felt presenting tailored information in a visual format, especially with graphs, would make the information easier for them to consume. For instance, when asked about potential improvements to her self-management app, Paula stated that she would "like to see visuals for my sugar levels – right now I need to know more than I do about the [numerical] readings." In this example, Paula felt that she would need to know more to understand her blood glucose readings, unless the app presented them in a visual format. Likewise, Rosa found a numbers-based presentation of glucose readings difficult to make sense of absent visual aids. Specifically, when asked what changes she would make to the tailored information, she stated she wanted "a yellow highlighter so I do not get confused with all the different readings." In this example, the highlighter would enable Rosa to visually mark key readings, such as recent blood sugar highs, out of a large diary of her blood glucose readings.

Second, participants felt color could aid them in using tailored information through the ability to quickly convey key information. For instance, when asked about ways he would change tailored information to better facilitate self-management, Burt stated:

[24] Mode tailoring is "adjusting information to match individual preferences for presentation modality, using verbal (text), visual (static illustrations), and/or audiovisual (videos) information" (Nguyen et al., 2017, p. 103).

> I would change the graph lines so the colors better show the [different blood glucose] zones – kind of like a stoplight. Green is good, yellow is making towards too high or too low, and red means trouble. The way it is now if a person goes to low they aren't looking at the phone, they are at the doctor!

This sentiment – that color could convey the meaning of tailored information – was shared by Roberta, who stated:

> [The app] uses different colors on the graph to point out your readings like the average… the only thing is they are hard to see, and those colors don't help me get better with what is going on with my average.

Roberta's statement reflects a perception that colors can help participants better understand tailored information. In conjunction, Roberta and Burt's statements demonstrate the way tailored information could use color to aid participants in understanding tailored information.

Third, participants experienced difficulty perceiving tailored information onscreen, making that information difficult to use. For instance, when asked about issues he experienced with tailored information, Bob stated "I can't see the numbers on the graph line, so I can't figure out my A1C." In this situation, Bob could see the graph but the numbers indicating the meaning of graph lines appeared too small, making it difficult for him to use the tailored information on the graph. Notably, Bob explained that an age-related visual impairment made using mobile devices with smaller screens problematic. Similarly, Rosa wanted to "be able to zoom better because I can't see the different things on the screen all that well." In this example Rosa found her mobile devices' zoom feature, which required spreading her fingers, difficult to control. Jim experienced a similar problem to Bob and Rosa, but it involved his wife who helped him use his app. Johnson stated, "it's [the app] only for one – I need my wife to help me and she can't see it on her device." Taken together, these three examples demonstrate situations where participants experienced difficulty using tailored information because they could not perceive the information onscreen.

Fourth, participants found the presentation of tailored information intrusive when apps pushed tailored messages to their mobile device. For instance, Rosa wanted:

> An app that would take a look at your medical history and curtail your messages and medication accordingly. I get all these messages [and don't know] what to do about it and they don't have nothing to do with me, I want to make them stop.

In this example, Rosa perceived the app as providing too many irrelevant messages and proposed tailoring the delivery of messages based on her medical history. Jill expressed a similar sentiment and found that tailored messages interfered with his sleep. She stated that she wanted to "change the alarm volume so it goes off when I need it or make it lower when I [don't need it]. It made me wake up when I was going to bed." Like Jill, Gina found alarms notifying her of tailored messages distracting, and stated "I'm happy to mute alerts so they don't mess with me." In conjunction, these examples show that participants perceived receiving too much tailored information, or using distracting notifications for tailored information, as problematic.

Main Issue 2: Distrust of Tailored Information

Next, participants expressed distrust of tailored information, especially in regard to the self-management recommendations of apps. These recommendations relate to key self-management behaviors, such as blood glucose management or diet. Problematically, apps often do not provide information about the basis for their recommendations. For instance, an app may recommend that a participant eat carbohydrates in response to their low blood sugar, but not reveal the information that informed that recommendation. Burt expressed this concern in stating that his app:

> gives me recommendations for my carbs or for a meal so that is helpful. But one thing with it is I have trouble with the bolus[25] recommendations, I can't figure out the base, so I don't know if I should trust it.

In this example, Burt did not know whether to trust tailored information regarding his carbohydrate intake because he lacked information about the recommendation. I asked Burt to further articulate his concerns about the consequences of trusting the recommendation. He replied, "yes, that's right, I don't want to mess up and cause an issue you know, you can get yourself in some trouble that way." This example demonstrates Burt's concern that trusting tailored information can cause an error in self-management leading to health issues. To protect his safety Burt indicated he did not follow the recommendation.

Likewise, Rosa encountered an issue with trusting the blood sugar recommendations made by her app. She stated:

> The readings for my sugar change to a smaller number because the decimal moves! I really want to make it how it was before, but don't know how, and I am not sure whether I should rely on the new number.

Similar to Burt, Rosa distrusted tailored information because she did not understand the basis of the app's recommendation. In this example, she did not know why the app moved the decimal point and did not revert to the original setting. One possibility is that she changed the

[25] Bolus describes "an extra amount of insulin taken to cover an expected rise in blood glucose, often related to a meal or snack" (American Diabetes Association, 2018).

measurement units used to record her blood glucose without realizing she did. For instance, the United States typically measures blood glucose in milligrams per deciliter (mg/dl) to measure glucose, while other countries use millimoles per liter (mmol/L) (Joslin Diabetes Center, 2018). However, the app did not provide sufficient context to Rosa about her blood sugar readings, and as a result she could not make this determination.

Ramona encountered a related issue with measurement and wanted to "adjust the insulin sensitivity with the units so it doesn't show up wrong". I asked Ramona to explain further and she said:

> I would love it if it would give me more digits for the insulin dose recommendations. So often I take a 100-unit dose when my sugar levels are too [low] before I eat a meal and the app [doesn't let me] go that high. Also, sometimes I'll take two doses…later in the day and it doesn't work for that.

In this example, the possibility that the app did not accurately measure his information created a lack of trust the app's output. Ramona indicated she did not follow the apps recommendations when this issue occurs because she lacked assurance about the recommendations.

Main Issue 3: Lack of cultural context for diet and physical activity made self-management difficult

Participants perceived that tailored information did not sufficiently account for their culture, especially in the context of managing their diet and physical activity. This lack of cultural context often made self-managing their diabetes with the app more difficult, as participants struggled to accurately track culture-specific behaviors. First, tailored information on diet involved a cultural context that participants perceived as key to self-management. Problematically, participants felt apps failed to account for this context. For instance, Paula stated “I [would] like apps that I can add what I’m actually eating to help me with my consumption, the [apps] don’t have the stuff I eat and [because I’m a] vegetarian.” When asked to elaborate, Paula explained that tailored messages on her diet, such as messages about her carbohydrate consumption, contained errors because the apps did not include her the meat substitutes she eats.

Similarly, Clyde stated “I eat a lot of eggs with breakfast, and I wanna be able to enter the number of eggs I eat in my omelet” while Rosa indicated that she wanted tailored messages that offered “more useful information of how to cook for [older diabetics] on a limited diet.” When asked to elaborate, Rosa explained that she drinks “a lot of soup broth made from animal bones and spices, especially when it gets cold” and that age-related dental issues make chewing solid foods difficult and time consuming. While apps enable participants to add food items, it requires participants to know the nutritional content of that food. Absent this nutritional information, tailored messages may contain inaccurate dietary or blood glucose recommendations.

Second, participants perceived that apps did not account for the types of physical activities they performed to manage their diabetes. Five participants described walking as their primary form of exercise, and discussed different types of walking, including exercise walking, walking outdoors, and mall walking. Participants wanted apps to distinguish between these different types of walking, as evidenced by Anna who wanted to, “add everyday walking and exercise walking because they lower you A1C [level].” When asked why she wanted her app to distinguish between these types of physical activity, Anna stated that she wanted to “better keep track of” her physical activity and that the two types of walking constituted distinct activities. Likewise, Burt wanted apps that “include my walking outside and working in the garden that I do for my exercise” so that he could better manage his blood glucose levels.

Main Issue 4: Barriers to using tailored apps for diabetes self-management

Next, participants perceived barriers that limited their use of tailored self-management apps, such as limited knowledge on using self-management apps, the cost of using self-management apps, and a lack of sufficient features to support self-management. First, Jack lacked experience and knowledge with using tailored self-management apps, and stated that he:

> needed help with apps, I have a 'hands on' class for diabetes [that] meets once monthly – [it] covers many, many aspects [of self-management] in a live setting. Some type of class would help [with] the apps, I have trouble with the technology.

Jack elaborated that while he attends a diabetes self-management education class through the YMCA, the curriculum only covers technology such as glucometers. Notably, Jack lacked experience with mobile devices in general, and felt he needed more general instruction on their functions.

Similarly, Kathy, a participant with less experience using self-management apps, said, "I need help with classes to teach me how to use [tailored diabetes self-management apps." In contrast with Jack, Kathy possessed experience with mobile devices, but lacked experience using tailored apps for self-management. Another group of participants attempted to use tailored self-management apps but stopped using them because of their limited knowledge of using their functions. For instance, Camila stated "I tried to and I am not able to use the apps" while Sandy stated "I do not have any [apps] on my mobile phone anymore because I couldn't figure it out." In conjunction, these statements evidence a lack of knowledge of tailored self-management apps as a barrier to self-management. As suggested by Jack and Kathy, classes or interventions offer an approach to overcoming this barrier.

Second, participants perceived apps' expense as a barrier to using apps, and a cohort of participants stopped using specific apps due to cost. For instance, Rosa stated:

> All apps [are] pretty much the same, but there are small adjustments in each one. I hate the cost of apps because I can't afford it on my budget. I don't understand why they can't be free.

Likewise, Elle felt that the "BG [app] is simple to use – I would like to see and be able to use apps without the cost. Cost, cost, cost…" while Carly stated, "I used Diabetes:M but a drawback was that I hate the cost. The [apps] seem the same but I hate the cost, so I don't use that app as much." Notably, the BG Monitor app requires a one-time fee of $5.99 while Diabetes:M app requires a monthly subscription that costs around $50 per year. When asked about app features he did not like, Burt bluntly stated "cost." In conjunction, these examples highlight that cost functioned as a barrier to using tailored self-management apps.

Third, participants felt apps' lack of self-management features functioned as a barrier to using apps. Specifically, when asked about barriers to using apps, Bob stated "[the app I use] doesn't let me input other things I need to track like my blood pressure, weight, and so on… I need to track these things also [along with] my sugar." Likewise, Johnson emphasized lack of self-management features for medications as a barrier, and complained his app had "no ability to track or add drugs [into the app]." Although a frequent user of self-management apps, when asked about potential barriers Rosa stated she "wish[ed] [the app] could track my physical exercise also, it tracks my sugar and meds." Taken together, these statements indicate participants perceived the lack of self-management features as a barrier to using tailored self-management apps.

To summarize, a number of main issues and sub-issues with mFIT V2 elements were identified. First, the problematic presentation of tailored information made information difficult to understand and use. Sub-issues included matching the modality used to present information to user characteristics and preferences, the use of color to convey tailored information's meaning, difficulty perceiving onscreen information, and the perception that apps that pushed information were intrusive. Second, a distrust of tailored information included issues such as a lack of information on the basis of app recommendations. Third, a lack of cultural context for diet and physical activity made tracking for self-management difficult. Sub-issues related to diet and physical activity not being sufficiently covered by an app. Fourth, barriers to using tailored apps for diabetes self-management included limited knowledge on using self-management apps, expense of diabetes management apps, and including too few self-management features. Table 19 presents these main issues and their corresponding sub-issues.

Table 19: Main issues and sub-issues issues identified for mFIT V2

Main Issues Identified	*Sub-Issues Identified*
Presentation of tailored information makes it difficult to understand and use	• matching the modality used to present information to user characteristics and preferences • the use of color to convey tailored information's meaning • difficulty perceiving tailored information onscreen • perception that apps that pushed information were intrusive
Distrust of tailored information	• Lack information on the basis of app recommendations

Lack of cultural context for diet and physical activity made tracking for self-management difficult	• Dietary choices not covered by app. • Physical activities not covered by app.
Barriers to using tailored apps for diabetes self-management	• Limited knowledge on using self-management apps. • Expense of diabetes management apps. • Too few self-management features.

Revisions to mFIT framework

To begin addressing the main issues identified by the older adult diabetics I made a set of four revisions to mFIT V2. I describe each revision below, along with revised definitions and examples that correspond with the update. At the end of this part I present mFIT V3, the product of these revisions (that was then subsequently tested in the next study with mobile app developers).

Revision 1: Modality tailoring

To address the issue of matching the modality used to present information to user characteristics and preferences, I included a new element called modality tailoring. In this context, modality describes the presentation of information using text, audio, video, or multimedia. In turn, I define modality tailoring as adapting the mode used to present information, such as text, audio, or video, for an individual's preferences or characteristics. This definition aligns with the way the tailoring literature defined recently described this issue as "adjusting information to match individual preferences for presentation modality, using verbal (text), visual (static illustrations), and/or audiovisual (videos) information" (Nguyen et al., 2017, p. 103). While extant tailoring elements center on adapting message content, tailoring modality deals with the way apps present participants with information. Examples of modality tailoring includes presenting text-based content in audio format for an individual with visual impairments or presenting text-based content as a graph in accordance with an individual's preferences.

Revision 2: Redefine contextualization to address distrust of tailored information

Next, I redefine and expand the contextualization definition to address participants' distrust of tailored information. As described above, the distrust of tailored information derived in part from a lack of transparency about the basis of tailored information. For instance, an app may conceal the blood glucose figures that inform dietary recommendations, causing a user to distrust those recommendations. Giving participants context about the basis of such recommendations could make tailored information more transparent and attenuate distrust. At present, mFIT defines contextualization as situating messages in a meaningful cultural context. I revise and expand this definition by adding a clause stating that contextualization "provides information and context about the basis of tailored messages." An example of this form of contextualization includes making it clear to participants which blood glucose readings inform an insulin recommendation. By including this clause, the revised definition states that contextualization "situates messages in a meaningful cultural context or provides information and context about the basis of tailored messages."

Revision 3: Combining evaluative and descriptive feedback

More participants indicated descriptive feedback facilitated diabetes self-management than any of the other tailoring elements. In contrast, no participant could articulate their support for evaluative feedback, even when specifically asked why they perceived evaluative feedback as supporting diabetes self-management. Further, the fewest participants perceived evaluative feedback as supporting diabetes self-management. To address this discrepancy, I combined evaluative and descriptive feedback into a single element named feedback, which I define as tailoring that "provides messages to participants about their psychological or behavioral states using participant data." This definition for feedback builds on the Harrington and Noar (2012) definition of feedback[26], but still makes explicit that feedback depends on user data. Under this new definition, an example of feedback could include a graph that depicts participant blood sugar readings over the past month. Likewise, a tailored message that states "your blood glucose is always high on the weekend" would also qualify as feedback. Along with clarifying the feedback element, this revision creates a more parsimonious mFIT framework.

Revision 4: Combining event-triggered dose and non-event-triggered dose

Next, no participant explained their support for event-triggered dose, and participants showed difficulty distinguishing between non-event-triggered dose and event-triggered dose. While three participants indicated they perceived event-triggered dose as facilitating diabetes self-management, these participants could not articulate why they found event-triggered dose supportive. This lack of support for event-triggered dose, along with an overlap between non-event-triggered dose and event-triggered dose, suggest a better approach combines these elements into a single dose element.

I identified the overlap between non-event-triggered dose and event-triggered dose because participants indicated the frequency they received messages to take medication depended on an event occurring, such as eating a meal. One participant asked that her information dose depend on her need to track blood glucose. In each example, non-event-triggered dose depends on the occurrence of event-triggered dose, so messages coded as event-triggered dose would necessarily receive codes for non-event-triggered dose. The examples

[26] Harrington and Noar (2012) defined feedback as "providing messages to participants about their psychological or behavioral states" (p. 336).

provided with the mFIT definitions further illustrate this issue. The example from the mFIT framework for event-triggered dose describes the situation where "an app sends a user a warning after they report an especially high glucose level." In this example, the frequency of tailored information depends on event-triggered dose, so any message coded as event-triggered information would necessarily be coded for non-event-triggered dose.

Combining event-triggered dose with the non-event-triggered dose element offers a solution to this issue. In this new approach, I define non-event-triggered dose as "tailoring the amount, frequency, sequence, and delivery system used to provide tailored information, along with tailoring the timing of information in response to an event." By integrating event-triggered dose and non-event-triggered dose into a single element, I eliminate the overlap issue described above. Additionally, combining elements creates a more parsimonious framework for evaluating tailoring.

mFIT Version 3

mFIT Version 3 includes six elements, five of which address tailoring type (feedback; content-matching; modality; personalization; and contextualization) and one element for dose. Table 20 below presents each tailoring type, along with the revised definitions and examples described above. As with the earlier versions of mFIT, these definitions and examples can function to code and score different tailoring types and dose, with each type receiving an unweighted score of one point. As a result, the total score for tailoring for mFIT V3 can range from 0-6.

Table 20: mFIT V3 elements

Tailoring Type	*Definition*	*Examples*

Feedback	• Provides messages to participants about their psychological or behavioral states using participant data	• A graph that depicts participant blood sugar readings over the past month • Message that states "your blood glucose is always high on the weekend"
Dose	• Tailoring the amount, frequency, sequence, and delivery system used to provide tailored information, along with tailoring the timing of information in response to an event.	• An app adapts the frequency it sends a user tailored messages based on their blood sugar.
Content-matching	• Messages tailored for constructs from health behavior change theories.	• "Your risk of developing co-morbidities will increase if you do not manage your diabetes."
Modality	• adapting the mode used to present information, such as text, audio, or video, for an individual's preferences or characteristics	• Presenting text-based content in audio format for visually impaired participants impairments.
Personalization	• A message that indicates a message is designed specifically for an individual.	• "We developed this message just for you, based on your dietary preferences and needs."
Contextualization	• situates messages in a meaningful cultural context or provides information and context about the basis of tailored messages	• You should eat more carbs because readings show your blood sugar is too low.

STUDY 3: TAILORING ELEMENTS DEVELOPERS PERCEIVE AS FACILITATING CHRONIC CONDITION SELF-MANAGEMENT AND REVISIONS

This section identifies the tailoring elements mobile application developers perceived as facilitating chronic condition self-management. First, I present the tailoring elements the developers perceived as facilitating diabetes self-management. In this section I also present the benefits the developers perceived in the mFIT V3 elements. Second, I present the main issues I identified with mFIT V3 through the the survey questionnaire and individual interviews. Third, I present a set of revisions to mFIT V3 to address these issues. Fourth, I present the fourth version of the framework, mFIT V4, which incorporates the revisions identified in the fourth step.

Perceptions of mFIT elements that facilitate diabetes self-management

The tailoring elements mobile app developers perceived as supporting diabetes self-management included feedback (*n* = 5), dose (*n* =4), content-matching (*n* = 3), modality (*n* = 3), personalization (*n* = 2), and contextualization (*n* = 2). Table 21 summarizes these results appears below.

Table 21: Tailoring elements developers perceived as facilitating diabetes self-management

Tailoring Type	*N(%)*
Feedback	5(50)
Dose	4(40)
Content-matching	3(30)
Modality	3(30)
Personalization	2(20)

Contextualization 2(20)

Next, the thematic analysis identified major themes in the qualitative data from the survey questionnaire and individual interviews. Major themes included two benefits I identified for mFIT V3. These benefits included developers' perception that content-matching and contextualization motivated improved self-management, and that developers perceived that dose benefited older adults by ensuring they received tailored information at vital times. Likewise, my thematic analysis identified themes that included the main issues I identified from the app developers' feedback. These main issue themes include users' selection of tailoring type and dose provided by apps, including feedback that identifies trends, and competition that promotes self-management.

mFIT V3 Benefits

Next, along with identifying the tailoring elements they perceived as facilitating self-management, participants also identified several benefits for the mFIT V3 elements. First, similar to the older adult participants, developers perceived content-matching and contextualization as motivating better self-management. Alejandro described this benefit by stating, "I believe that content-matching… is the most important tailoring type. The reason is that it motivates users to do their best in implementing lifestyle changes or pharmacological interventions." Mia perceived a similar benefit from both content-matching and contextualization and stated she felt these elements "can be used to induce and motivate desirable behavior changes." Taken together, these statements suggest content-matching and contextualization can motivate improved diabetes self-management.

Second, participants perceived that dose benefited older adults by ensuring they received tailored information at vital times, especially through the use of event-triggered dose. For instance, Ava strongly felt dose "is needed to make sure medications and measurements are taken on time. It is very important!" Ava felt that dose benefits older adults because they receive timely warnings and recommendations they otherwise might forget or miss. Absent such warnings, Ava expressed concern that an older adult might forget to perform a self-management behavior. Isaac expressed a similar sentiment in stating that dose "can be used to inform the user about their current health status and potentially issue warnings and/or suggest preventive measures." Notably, both examples describe event-triggered dose.

Main Issues Identified

Along with developers' perceptions about the mFIT V3 elements, my analysis identified three main issues developers found with mFIT V3. These main issues included enabling users to choose the types and dose of tailored information provided by apps, a need to include feedback that identifies trends, and the use of competition to motivate self-management. I describe each main issue in depth below.

Main Issue 1: Users choose tailoring type and dose provided by apps

A number of developers advocated for users selecting the type and dose of tailoring provided by apps. In this perspective, an app gives users the autonomy and flexibility to decide which tailoring types and dose best support their diabetes self-management. At present, mFIT V3 does not include this perspective. Maya proposed this approach by asking:

> how about leaving the option for users to tailor types as they see fit? If there's enough resources to develop the app on the backend, leave the option to the user to decide which type they see fit instead of picking and choosing from this list [of tailoring elements].

Similarly, Irene, a nurse that developed a diabetes self-management app for her hospital, asked, "why not just have the users make the decisions about the tailoring? That way they can control the tailoring they get." On asking Irene to elaborate, she explained:

> We currently are working on a hospital app and… program recognized by the American Diabetes Association. Part of that program is to follow-up with the patient. The questions are asked by phone and we feel like the perception is we are bothering them. We also have to track how many attempts we made. Given this experience, I think a much simpler method for tailoring would be to put the ball in the patient's court and ask them to choose the tailoring they wish.

In this perspective, Irene perceived a benefit to user-controlled tailoring because she found this approach less intrusive for users. Additionally, she advocated for the simplicity of users choosing their tailoring elements. When asked to explain what simplicity meant in this context, she stated "letting the patient decide makes it so we don't have to figure out ahead of time what they want." From Irene's perspective, letting users choose their tailoring elements limited the demands placed on developers to determine the most effective tailoring types.

Main Issue 2: Feedback that Identifies Trends

Next, a third of the developers perceived that identifying trends could benefit participants, but problematically mFIT V3 does not recognize such trends. In this context, I use trends to describe apps identifying patterns in participant data over a period of weeks or months. Franklin, a 50-year-old developer with diabetes working from Tuscon, suggested incorporating trends into mFIT and stated:

> About the only thing I can think to add is historical trending context over varying time periods... For instance you weigh 175 now, that's down 7 pounds in the last 120 days.

> Or you've exercised 240 minutes this week, that's up week over week, etc… the feedback I got after release of StickBuddy caused me to add a few of these types of roll up numbers (with green up arrows and red down arrows to indicate trending up or down).

When asked about the benefits of using trends, in comparison to other types of feedback, Franklin continued:

> I was using more fast acting insulin per day than I was 3 months ago earlier this year. What's up with that? Insulin resistance? Have I been eating worse than normal? Turns out the fridge I was keeping my fast acting in was not keeping as cool as it should (in the garage in Tucson – go figure) – it's overall effectiveness had fallen off after being in there for several months and I was having to take more units a day to keep up. I was able to verify this by buying new Novolog[27] (out of pocket – thanks private insurance), keeping it in my internal fridge and watched my numbers come back into line. I might not have noticed that trend otherwise as the amounts were within reasonable numbers that vary naturally based on what I'm eating and activity/stress levels.

Franklin's example shows the potential benefit of trends for recognizing patterns that otherwise go undetected. By examining participant data over several months, patterns emerged that enabled Franklin to identify a significant issue with his insulin and blood glucose levels.

Similarly, Sandy perceived that identifying trends would lead to benefits. While Franklin used trends to identify issues with his insulin and blood glucose, Sandy used trends to identify where she pricked herself to check her blood glucose.

> I wrote [my app] for keeping track of where I personally prefer to inject and stick for blood checks and to keep track of which of those locations have been used and which

[27] Novolog is a type of insulin sold by Novo Nordisk

> ones are next. Over the years I had developed callouses on my fingers from too frequent use of easy-to-access stick locations and lumps under the skin from over use of some injection sites. Identifying trends in where I was sticking myself over time helped with this issue.

As with Franklin, Sandy used trends to identify trends to identify potentially useful patterns that occur over a period of time, such as months.

Main Issue 3: Competition to Motivate Self-Management

Along with trends, several developers proposed that apps provide tailored information to facilitate competition between users. These developers felt competition with other app users could increase participants' motivation for self-management. For instance, several developers felt a users' desire to outperform their peers could motivate users. Discussing motivation, Alejandro stated he felt apps should include features "that compare someone's results with that of [their] peers. If this is the case, this might be called 'competitive tailoring.'" In this perspective, participants compete against each other to best self-manage their diabetes.

Several participants described such competition in terms of gamification, with the idea that gamification of self-management could function to motivate users. For instance, Franklin felt motivated by an app feature that made a game of comparing users' exercise levels. This game used an arrow that changed colors to depict participant's relative positions. Franklin stated:

> For reasons I can't quite explain folks find these motivating – even myself after scoffing at these simplistic "gamification" tactics that I tend to scorn [I] found myself watching that stupid arrow on my exercise time for the week and actually caring if it was red or green.

Similarly, Cal proposed that competition – again in the form of gamification – could motivate self-management.

> I use the exercise metric myself but not the others due to complexity [of] manual input [for] things like carb intake and the like. I'd characterize this… as a "gamification" approach to motivate tailoring – and it can be effective. Ben and Brian had wanted to post some of these numbers to a web service for competitive reasons, but this was a bridge way too far for me – and since I was the developer it didn't happen.

Notably, Cal also used exercise as an example for competition and gamification.

Table 22 below summarizes the major categories of issues identified in this part and provides a description for each issue. These issues include users' choice of tailoring type and dose provided by apps, feedback that identifies trends, and the use competition that motivates self-management. In the following section I propose a set of revisions to address these issues.

Table 22: Main issues identified by developers

Main Issues	*Description*
Users choose tailoring type and dose provided by apps	• In this approach, users rather than developers determine the type and dose of tailoring provided by an app. This approach may make apps less intrusive and better suited for participants' information needs.
Feedback that identifies trends	• Trends identify patterns in participant data over a period of weeks or months. This approach could benefit older adults that otherwise may not detect a trend in their behavior.
Competition that motivates self-management	• Facilitating competition between older adult participants can facilitate self-management by increasing motivation.

Revisions to mFIT V3

To begin addressing the main issues identified with mFIT V3, I made a set of three revisions to mFIT V3 that I describe below. Additionally, this section includes revised definitions and examples for the tailoring elements. At the end of this section I present a fourth version of the mFIT framework, mFIT V4, that incorporates these revisions.

Revision 1: Add user choice to dose

Several developers advocated for enabling users to choose tailoring types, rather than the app developers. mFIT V3 does not account for user-choice and relies on the app's algorithm to determine which tailoring types an app provides. To address this issue, I added user-choice to the dose element. Under this perspective, if an app allows a user to choose the tailoring type, it will count as tailoring dose. For instance, an app may allow a user to choose whether they want to receive feedback on their weight as part of their self-management. Such an app would receive a score for the dose element for providing the user with this choice.

Revision 2: Add trends to feedback

Along with adding user choice to dose, I intend to expand the feedback element to encompass trends. I define trends as tailoring that provides messages to participants about patterns in their psychological or behavioral states that occur over a period of time. For the purpose of this revision, I added an example of a trend, but did not alter the definition of feedback. I did not alter the definition of feedback because the current definition encompasses trends. Examples of messages describing a trend might include "you have lost five pounds each week for the past three months" or "you have managed your blood pressure better for the past five months than this time last year." I intend for such messages to qualify as feedback in mFIT V4.

Revision 3: Add competition to feedback

Similar to adding trends to feedback, I expand the feedback element to include competitive tailoring. As with trends, I did not alter the definition of feedback, but use examples to clarify that I intend for the feedback element to encompass what the developers described as competition. Further, competitive tailoring overlaps with the comparative feedback element included in mFIT V1. I combined comparative feedback and descriptive feedback into a single element called feedback in the first step of this results section. I define competitive tailoring by building on the comparative tailoring definition as, "comparing an individual's data with their peers to motivate improved self-management". An example of competitive tailoring would be a message stating that "you eat more sugar than Carl does, see if you can eat less sugar than Carl." This message would qualify as feedback under mFIT V4 because it uses peer information to motivate the user to improve their diabetes self-management.

mFIT V4

mFIT V4 includes six elements, five of which address tailoring type (feedback; content-matching; modality; personalization; and contextualization) and one element for dose. Table 23 below presents each tailoring type with their corresponding definition and examples.

Table 23: mFIT V4 elements, definitions, and examples

Tailoring Type	*Definition*	*Examples*
Feedback	• Provides messages to participants about their psychological or behavioral states using participant data.	• A graph that depicts participant blood sugar readings over the past month • Message that states "your blood glucose is always high on the weekend" • "You have lost 7 pounds a week for the past month"

		• "You ate more sugar than Carl last week, try to eat less than him this week."
Dose	• Tailoring the amount, frequency, sequence, and delivery system used to provide tailored information, along with tailoring the timing of information in response to an event. Users may also choose tailoring types.	• An app adapts the frequency it sends a user tailored messages based on their blood sugar.
Content-matching	• Messages tailored for constructs from health behavior change theories.	• "Your risk of developing co-morbidities will increase if you do not manage your diabetes."
Modality	• adapting the mode used to present information, such as text, audio, or video, for an individual's preferences or characteristics	• Presenting text-based content in audio format for visually impaired participants impairments.
Personalization	• A message that indicates a message is designed specifically for an individual.	• "We developed this message just for you, based on your dietary preferences and needs."
Contextualization	• Situates messages in a meaningful cultural context or provides information and context about the basis of tailored messages	• You should eat more carbs because readings show your blood sugar is too low.

CHAPTER SUMMARY

This chapter provided the results from the content analysis, along with surveys and individual interviews with older adults and developers. First, I presented the content analysis results, which identified the benefits of mFIT V1, along with the main issues with evaluating apps using mFIT V1. I identified seven revisions for mFIT V1 based on these findings. Subsequently, I developed mFIT V2, which included seven elements. Second, I presented the results from the survey questionnaire and individual interviews with older adult diabetics. This part identified the tailoring elements from mFIT V2 that older adult diabetics perceived as facilitating diabetes self-management. I also identified the benefits and main issues with mFIT V2. Based on these issues, I revised the framework a second time, developing mFIT V3, which used six elements. Third, I presented the results from the survey questionnaire and individual interviews with developers. This part identified the tailoring elements from mFIT V3 the developers perceived as facilitating self-management, while also identifying the benefits of mFIT V3. I also identified the main issues with mFIT V3. I addressed these main issues with set of revisions, producing mFIT V4, which also uses six elements.

To complement mFIT V4, I developed an evaluation form for coding chronic condition self-management apps. This revised form includes six items, five of which address tailoring type, and one of which address elements of dose. Each item coded 'Yes' on the form will receive an unweighted score of one point, producing a total score ranging from 0-6. This revised evaluation form appears in table 24.

Table 24: mFIT V4 Evaluation Form

Use this table to evaluate tailored chronic condition self-management apps. Answer the following questions by placing an "X" in the appropriate column →	Column A	Column B
1. Does the app tailor for feedback?	Yes	No
2. Does the app tailor for dose?	Yes	No
3. Does the app tailor for content-matching?	Yes	No

4. Does the app tailor for modality?	Yes	No
5. Does the app content for personalization?	Yes	No
6. Does the app tailor for contextualization?	Yes	No
• Assign 1 point to each "X" in Column A for Questions 0-6; • Total the final points, which should range from 0-6; this is tailoring type total:_______________ • Higher scores indicate an app tailors for more types and elements of dose		

Chapter 6: Discussion

This dissertation study developed a theory-based framework for evaluating the type and dose of tailored information provided by chronic condition self-management apps. The findings from this study informed the development of the mHealth Framework for Investigating Tailoring (mFIT), which offers a novel approach to evaluating tailored information. The findings also confirm this framework can evaluate and quantify tailored information provided by diabetes self-management apps. Further, despite proposed reporting standards for tailoring studies (Harrington & Noar, 2012), the mHealth Framework for Investigating Tailoring (mFIT) marks the first known framework that evaluates and quantifies the type and dose of tailoring provided by mobile apps. Such a framework contributes to identifying the mechanisms that support tailoring, and to the development of effective tailored diabetes self-management interventions.

In this chapter I discuss the implications of my findings for mFIT V4, along with technology-based approaches to self-management and age-related self-management challenges. First, I discuss the different purposes mFIT serves, and the way mFIT facilitates the needs of key stakeholders, including older adults with diabetes, app developers, and researchers. Second, I discuss the theoretical implications for mFIT V4, and present an updated tailoring model that builds on the message effects model. Third, I discuss the findings in the context of technology-based approaches to diabetes self-management. In particular, this part explores the implications of the findings in relation to the benefits and challenges of diabetes self-management. Fourth, I discuss the findings in the context of ways tailoring can address age-related challenges to diabetes self-management. Specifically, I examine the way tailoring can address cognitive and sensory declines. Fifth, I present study limitations and future directions for this research.

mFIT Purpose

The findings confirmed that mFIT can achieve different purposes for key stakeholders, such as researchers, older adult diabetics, and chronic condition mobile app developers. First, the tailoring definition developed with the mFIT framework aids researchers with operationalizing tailoring. Despite numerous proposals, tailoring lacks a consensus definition, e.g., Noar et al., (2009), making the concept's scope unclear. Researchers' difficulty distinguishing between targeting and tailoring, e.g., Hawkins et al., (2008), Kreuter & Skinner, (2000) reflects this scoping issue. By revising tailoring's definition, I argue that tailoring is best described as a *process* for adapting information, not the *product* of that process. Adopting such a definition can provide a foundation for future tailoring research.

Second, the findings demonstrate that researchers can use mFIT to evaluate the impact of different dose elements and tailoring types on diabetes self-management. The content analysis reflects mFIT's potential ability to evaluate and quantify the type and dose of tailoring provided by an app by evaluating and scoring 20 diabetes self-management apps. Using these abilities, researchers can use mFIT-guided interventions to identify the relative impact of the mFIT constructs, or interactions between different mFIT elements. This ability improves on the proposed reporting standards, which did not offer a comprehensive framework to evaluate tailoring type or address the concept of dose (Harrington & Noar, 2012). Likewise, the message effects model never included a concept of dose (Noar et al., 2009). Further, researchers never implemented the proposed reporting standards to report study results, so their usefulness for identifying tailoring's mechanisms remains circumscribed (Harrington & Noar, 2012). The mFIT framework eliminated this issue by not relying on researchers to report results with the framework.

Third, developers can use mFIT to guide the design of tailored chronic condition self-management apps. Developers can use mFIT to determine the tailored information an app provides, which in turn could improve understanding of the mechanisms supporting tailored chronic conditions self-management apps. While the proposed reporting standards described different tailoring types (Harrington & Noar, 2012), as did the message effects model (Noar et al., 2009), researchers did not develop those standards specific to mobile apps. By designing the mFIT framework specific to mobile apps, mFIT possesses advantages over frameworks lacking a specific technological focus. For instance, mFIT includes concepts such as frequency and sequence for dose. Such concepts may possess greater relevance with mobile apps, which can deliver information with greater speed than alternate modalities, such as print letter.

Fourth, mFIT integrates the input of key stakeholders, such as older adult diabetics and mobile app developers, which provides advantages over other tailoring frameworks. Researchers developed the proposed reporting standards through a literature review, which were then reviewed by an advisory board of tailoring researchers (Harrington & Noar, 2012). Notably, these proposed standards lacked stakeholders' input, such as older adult diabetics or mobile app developers. As demonstrated by this study, stakeholder input can provide a unique and essential perspective. For instance, developers perceived user's choice of tailoring types as an important concept for mFIT to address. Absent these developer's input, mFIT would not address this potentially impactful concepts.

THEORETICAL CONTRIBUTIONS FOR MFIT VERSION 4

In this section I use my findings to update and extend the message effects model (Noar et al., 2009). An updated model can provide theory-based support for the revised mFIT framework and begin to address the factors masking tailoring's mechanisms. These factors included using theory to develop messages rather than explain tailoring (Lustria et al., 2013; Krebs et al., 2010; Noar et al. 2009), and a reliance on extant models, such as the elaboration likelihood model (Lustria et al., 2013; Noar et al., 2007), to support tailoring. Likewise, the message effects model specifically addresses tailoring (Noar et al., 2009), but remains unevaluated in empirical studies. In this section I revise the message effects model with my findings, integrating potentially key, novel concepts, such as dose, to inform the model. I also propose that mFIT elements impact specific constructs along the updated path model.

The updated message effects model uses two routes to describe the way individuals process different types and doses of tailored information, the central and peripheral routes. First, the central route engages when individuals perceive a tailored message as personally relevant. This route increases attention to a message and motivates individuals to elaborate, and in turn, individuals consider the message's arguments. This process results in greater information seeking, along with behavior and attitude change, for arguments perceived as strong by individuals. Notably, the central route matches the way the message effects model described processing tailored information. The theoretical foundation for this route derives from the elaboration likelihood model and the McGuire (1968) model of persuasion.

Second, the peripheral route engages when individuals perceive a message as relevant but do not devote resources to processing that message. Under the elaboration likelihood model, engaging the peripheral path correlates to individuals directing fewer cognitive resources towards a message, attenuating that message's impact. However, messages processed by the peripheral path may benefit individuals that evaluate messages heuristically, without consideration of argument strength. The heuristic-systemic model provides support for this perspective by proposing that some individuals use a heuristic approach to evaluate messages

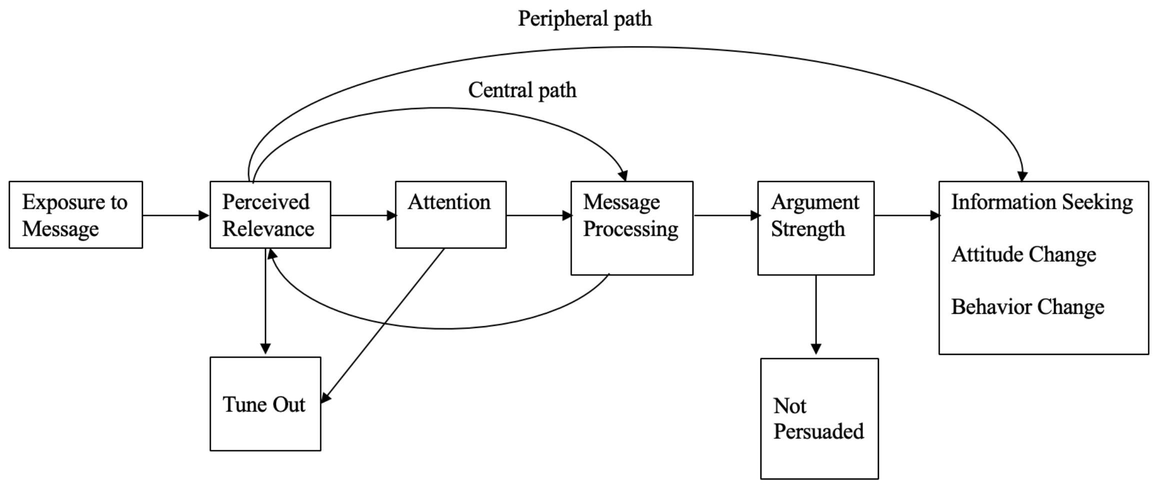
(Hooper et al., 2013). This approach relies less on cognitive resources and more on contextual factors, such as the information source, to evaluate a message (Hooper et al., 2013). Other support for this perspective includes a randomized controlled trial of a tailored, web-based intervention promoting screening for sexually transmitted diseases that found perceived relevance significantly increased outcome measures, such as behavioral intention, without individuals devoting additional attention to, or elaborating on, a message's arguments (Lustria et al., 2016). This result suggests tailoring can impact outcomes even in situations where individuals do not consider a message's arguments.

The dose element also supports including the peripheral path with the message effects model. Using the peripheral path, tailored messages that rely on low doses of tailored information may directly impact outcome measures when message content requires less processing. For instance, participants may follow the direction of an urgent message that instructs them to visit to the doctor because of an emergency without careful consideration that argument's merits. Rather, such a participant may rely on heuristic factors, such as the information source, to evaluate the merits of this message. In this scenario, a participant may trust information provided by their self-management app and decide to follow the message's instruction without carefully processing the message. Placebo tailoring, which uses personalization to make generic messages appear tailored, may also rely on the peripheral path for support. From this perspective, individuals perceive personalized messages as personally relevant and follow the message's recommendations without careful consideration of the message's arguments.

Likewise, my findings on the problematic presentation of tailored information support the addition of a peripheral path to the message effects model. Specifically, participants perceived that color could quickly and simply convey meaning without relying on verbal explanations that require cognitive resources. For instance, a message that uses a red background to urge a participant to visit the doctor conveys urgency without relying on the participant's careful processing of that message. Rather, the color red conveys the urgency and importance of the message, obviating the need for the participants to devote additional cognitive resources to message processing.

Figure 6 below presents a path model for this revised message effects model. This model begins with an individual's exposure to a message, during which they evaluate the relevance of a message (Noar et al., 2009). If an individual perceives a message as relevant, they attend to the message and devote cognitive resources to message processing. Further, a cyclical relationship exists between perceived relevance, attention, and message processing, such that increased message processing leads to additional relevance assessments. Next, participants evaluate message arguments, with persuasive arguments producing gains for information seeking, attitude change, and behavior change (Noar et al., 2009). Alternately, individuals may process messages perceived as low relevance through the peripheral route (Lustria et al., 2016). This route may produce increased information seeking, attitude change, and behavior change for individuals that process messages through emotion rather than careful consideration of the message. Consistent with this perspective, the peripheral path bypasses consideration of argument strength.

Figure 6: Revised message effects model



Next, I propose that the six mFIT tailoring elements may influence specific constructs along this path model. This proposal builds on the message effect model, which posited that four tailoring types impact specific constructs (Noar et al., 2009), but did not clarify the role of key constructs, such as feedback or dose. First, content matching can make messages more effective by using health behavior theories to improve argument strength and develop more convincing arguments (Noar et al., 2009). Second, personalization can influence both perceived relevance and attention, as participants attend to messages with personalized characteristics, such as name and gender, and perceive such messages as relevant to themselves (Noar et al., 2009). Third, contextualization may also influence perceived relevance and attention. This may occur as participants perceive messages situated in a familiar cultural context as more relevant and attend more closely to those messages. Contextualization may also make message processing more efficient, as participants can better process messages written in a familiar language or dialect. Fourth, I propose that feedback impacts argument strength by making arguments more compelling. Findings that involved feedback, such as identifying trends in behavior over time, align with studies suggesting feedback can provide participants with novel insights into their behavioral or psychological states, e.g., Harrington & Noar, (2012). Along with making participants more aware of their behavior and psychology, including this information may strengthen arguments asking participant to perform self-management behaviors.

Fifth, the modality used to present information may impact perceived relevance, attention, and message processing. The prior approach to the message effects model asserted that adapting the design, production, and channel of information can increase attention and message processing, citing a meta-analysis with evidence that the inclusion of visual elements attracts attention (Noar et al., 2009; Noar et al., 2007). While the modality element does not account for the design or production of tailored information, it does impact the way apps present tailored information, and would be likely to influence attention and message processing as well. Additionally, I propose that modality influences perceived relevance, as individuals are more likely to perceive messages presented in a medium they can comprehend as relevant. For instance, a participant with visual impairment may perceive that content presented in a medium they can consume as relevant.

Sixth, I propose that dose impacts constructs that include perceived relevance, attention, and message processing. Tailored apps that provide too high a dose of information could lead participants to perceive messages as irrelevant. Such a scenario could occur if an app sends tailored messages too frequently, creating stress for a participant who then ignores those messages as a coping mechanism. This scenario aligns with the information overload literature, which found that overload can create and stress and anxiety (Misra & Stokols, 2011; Bawden & Robinson, 2009). Likewise, too much information could make attending to a message and processing that message problematic. Longer messages require additional cognitive resources to process those messages (Schick & Gordon, 1990) and participants may lose interest and not attend to messages with too much information.

Table 26: mFIT elements and corresponding constructs

Tailoring element	*Outcomes*	*Key variables*
Content matching	Argument Strength	Stages of change, attitude, self-efficacy, social support and processes of change
Personalization	Perceived relevance and attention	Gender, age, race, cultural norms
Modality	Perceived relevance, attention, message processing	Images, illustrations, video, text
Dose	Perceived relevance, attention, and message processing.	Amount, frequency, sequence of information provided, event-triggered information, user choice, and delivery system used to provide tailored information.
Contextualization	Perceived relevance, attention, and message processing	Diet, physical activity, language
Feedback	Argument strength	Participant data

A TECHNOLOGY-BASED APPROACH TO DIABETES SELF-MANAGEMENT INTERVENTIONS

Along with tailoring, the findings extend the literature on technology-based approaches to chronic condition self-management. Technological developments, such as decision support features, can facilitate self-management among older adults by addressing their age-related differences in cognitive, motor, sensory, and social changes (American Diabetes Association, 2014). In this part, I situate these findings in the literature on technology-based interventions. In light of these findings, I revisit the benefits and challenges technology presents for older adults self-managing diabetes.

The decision support features of technology-based interventions may offer older adults key benefits, but this research found trust issues exist with information produced by these processes. Information generated by decision support features include suggestions for insulin, carbohydrate consumption, or physical activity (El-Gayar et al., 2013), and decision support features integrate contextual information about individuals such as an individuals' location or time of day to develop these recommendations (Dennison et al., 2013). Despite potential benefits, the findings demonstrated that participants may distrust recommendations when apps conceal the basis for recommendations. Consistent with these findings, a recent meta-analysis found most apps do not validate users' input (Huckvale et al., 2015), and user error inputting information could lead to erroneous or dangerous recommendations. For instance, a user might accidentally record low blood sugar because neuropathy in their fingers that makes inputting information digitally difficult. Such a user would receive insulin dosage recommendations based on inaccurate information, creating a potentially dangerous situation. Similarly, apps often make recommendations based on incomplete information (Huckvale et al., 2015). For instance, an app may recommend that a user take insulin if a user forgot to track an earlier dose, which results in double dosing. These potential issues validate older adults' concerns of tailored information and suggest increased transparency as a solution. Along with transparency, asking users to confirm the accuracy of information used for tailoring could provide an important safety mechanism.

More broadly, the findings on older adult diabetics' distrust of tailored information extend the literature on older adults' trust issues with web-based health information. Prior studies involving trust have examined older adults' distrust of sharing health information in specific contexts, such as on social media or by mobile devices. For instance, distrust of tailored information aligns with the results of a study investigating older adults' perceptions and learning of social media (Xie et al., 2012). Participants in that study expressed a distrust of Facebook and YouTube, with concerns about social media corporations' commodification and exploitation of their private intimate information (Xie et al., 2012). Similarly, an analysis of the Health Information National Trends Survey found that factors that influence sharing health information by mobile devices include higher age, educational attainment, and socioeconomic status (Serrano et al., 2016). Specifically, older age correlated with less willingness to share electronic health information, while more educated participants and those with higher socioeconomic status displayed a higher willingness to share such information (Serrano et al., 2016).

Although older age may impact trust in health information, a more complicated picture emerges when considering health and eHealth literacy. For instance, an online survey of African-American and Caucasian individuals ($N = 811$) investigated the relationship between eHealth literacy and perceived trust in online health information sources (Paige, Krieger, & Stellesfson, 2017). Notably, this survey found that age did not independently impact perceived trust in online health information, except when also considering eHealth literacy. Rather, older adults with high health literacy demonstrated similar perceived trust to other age groups, while older adults with low health literacy demonstrated significantly lower perceived trust in online health information sources than younger age groups. These results align with the findings of Xie et al. (2012), where older adults expressed distrust of online health information sources, such as Facebook and YouTube. Participants in that study consisted primarily of older adult with little Internet experience (Xie et al., 2012). In contrast, a survey conducted as part of a larger study on differences between rural and urban health information use found that participants ($N = 600$) with low health literacy trusted health information sources such as social media and the television, but distrusted healthcare professionals (Chen et al., 2018). In conjunction, these studies suggest a complex relationship between health literacy, age, and trust in technology-mediated health information that requires extensive further investigation.

A greater variety of methodological approaches may help clarify this trust issue. Many recent studies use cross-sectional surveys, e.g., Chen et al., 2018; Paige, Krieger, & Stellesfson, 2017; Serrano et al. 2016, that provide only limited insight into contextual factors surrounding older adults, trust, and eHealth literacy. Methods that produce qualitative data, such as interviews, can provide a necessary, additional perspective, as demonstrated by (Xie et al., 2012. In that study, older adults met weekly for open-ended discussions over seven weeks, enabling researchers to explore participants' evolving perspectives on social media Xie et al. (2012). A similar approach could help explore and better understand issues of trust in tailored information and eHealth literacy.

Next, in contrast with trust, no privacy issues emerged among participants over technology-based self-management interventions, despite these interventions' reliance on tracking intimate health information. Potential explanations include older adults' inexperience with privacy issues and precautions, consistent with lower smartphone use than other age cohorts (Anderson & Perrin, 2017). This explanation aligns with a study that found older adults comprise the group least likely to conceal their identity online (Rainie et al., 2013), and suggests some users may lack awareness of potential threats. Another potential explanation is that older adults that use smartphones are typically wealthier, better educated, and younger (Anderson & Perrin, 2017), so the cohort using phones is already aware of the privacy concerns.

Along with privacy, these findings highlight the key role culture plays in effective technology-based approaches to diabetes self-management interventions. Specifically, participants perceived that tailored apps ignored key cultural items with diet and physical activity, especially for participants tracking their behavior. Participants felt this oversight made accurately tracking their information difficult. For instance, an app might lack the ability to track culturally specific physical activities, such as ballroom dancing or exercise walking. In turn, this issue risks producing tailored information of questionable quality. Notably, these findings deal with tracking data used for tailoring, an issue distinct from cultural tailoring, defined as "contextual influences… that may influence the way individuals understand and process health information" (Kreuter et al., 2005) or simply "tailoring on cultural variables" (Davis et al., 2011). Rather, the current study's findings suggest a key consideration in developing technology-based tailored interventions is ensuring the cultural relevancy of items used to tailor information. One approach to addressing this issue in future studies includes using focus groups and pilot testing for the items used to tailor information.

Culture aside, the findings support that low eHealth literacy erects barriers to participating in technology-based diabetes self-management interventions. Consistent with past work that found higher age correlates to lower health and eHealth literacy levels (Kutner, Greenberg, Jin, & Paulsen, 2006; Neter & Brainin, 2012), and that low health literacy aligns with less Internet use (Levy, Janke, & Langa, 2014), older diabetics perceived a lack of knowledge about self-management apps as a barrier to intervention participation. A potential solution to this issue includes educational interventions that improve older adults' knowledge about self-management apps. Such a solution aligns with the literature on eHealth literacy interventions that indicates interventions can improve eHealth literacy (Watkins & Xie, 2014), and a recent survey that found half of older adults perceive they need help using new technology (Smith, Anderson, & Page, 2017). Alternately, a content-based approach could include adapting messages for user literacy levels, such as occurs with tailored messages.

Similarly, the findings suggested that costs function as a barrier to technology-based self-management interventions, despite the potential benefit savings provide for those delivering interventions (Nundy et al., 2014). Specifically, participants' perception of costs as a barrier to participation evidenced the continued need to develop more cost-effective approaches to delivering interventions. Further, these findings show that while mHealth offers potential savings for providing interventions (Nundy et al., 2014), these savings must pass to participants for effective interventions to occur. Additionally, wealthier older adults use smartphones at much higher rates than less financially secure older adults (Anderson & Perrin, 2017), suggesting that lower socioeconomic status older adults already face exclusion from mHealth interventions due to costs.

TAILORING AND DIABETES SELF-MANAGEMENT AMONG OLDER ADULTS

Similar to technology-based approaches, the findings suggest tailoring can offer an effective strategy for overcoming age-related limitations to chronic condition self-management, such as changes in cognition or motor ability. Notably, the findings suggest that tailoring modality can help address some age-related sensory changes, such as visual or auditory declines. For instance, individuals that suffer from visual decline may benefit from tailored information presented in an auditory rather than a visual medium. Given that one-fifth (19%) of older adult diabetics suffer from visual declines (Center for Disease Control and Prevention, 2012), and hearing declines impact a third of older adults age 65-74 (National Institute on Deafness and Other Communication Disorders, 2012), modality tailoring could extend tailored interventions to older demographics that previously struggled with accessing and using interventions.

Likewise, the findings suggest tailoring can facilitate self-management among older adults experiencing age- or diabetes-related cognitive declines. In particular, the feedback element may support older adults in identifying patterns in their behavior that otherwise might be difficult to detect in the context of decreasing working memory, executive function, and attention (Wong, Scholey, & Howe, 2014). For instance, an app may alert an individual that they do not regulate their blood sugar well during weekends. Identifying and addressing such an issue may pose particular difficulties for individuals with memory issues, which indicates that such an alert could provide an important support mechanism. Dose of tailored information may also provide a mechanism for adapting interventions to participants with cognitive changes. For instance, more frequent messages may serve as a beneficial reminder to perform self-management activities for older adults with memory declines. Alternately, providing too high a dose could burden individuals' cognition if the messages distract or overload participants with information. Future research should clarify the role dose plays in this context and the ways dose can support cognition among older adult diabetics.

The findings also evidence a need to clarify the role peers play in facilitating chronic condition self-management among older adults. App developers proposed that apps facilitating competition among peers could improve individuals' motivation to perform self-management activities. However, under such a perspective, individuals may view peers as a source of competition rather than social support. Social support may play a key role in diabetes self-management, with greater social support linked to improved self-management (Baek, Tanenbaum, & Gonzalez, 2014; Tovar, Rayens, Gokun, & Clark, 2013; Schiotz, Bogelund, Almdal, Jenson, & Williang, 2012; Strom & Egede, 2012). Similarly, social isolation can worsen behavioral and psychological outcomes for older adults (Shankar et al., 2011; Cornwell & Waite, 2009). Consequently, researchers must clarify whether competition amongst peers attenuates social support and promotes social isolation or catalyzes self-management.

Alternately, individuals may understand competition as a form of social support and enjoy the benefits of both social support and competition.

METHODOLOGICAL CONTRIBUTIONS

The methodological approach developed for this study offers key strengths as demonstrated by the findings. Specifically, this research followed a novel, mixed-methods approach to investigating tailored apps with three sequential steps. Mixed methods approaches involve "research in which the investigator collects and analyzes data, integrates the findings, and draws inferences using both qualitative and quantitative approaches or methods in a single study or program of inquiry" (Tashakkori & Creswell, 2007, p. 4). After developing mFIT V1 through the literature review detailed in chapter 3, this mixed-methods approach ensured subsequent mFIT versions integrated the perspectives of older adult diabetics and mobile app developers, while also confirming mFIT can evaluate and quantify tailored information. More generally, these benefits aligned with the perspectival strengths of mixed-methods approaches, that leverage the strengths of qualitative and quantitative data to minimize each respective approaches' limitations (Pluye & Hong, 2013; Creswell, Klassen, Clark, & Smith, 2011).

Along with improving mFIT, this mixed-methods approach revealed key contextual information on challenges older adults face in processing tailored information. Such contextual information can illuminate aspects of the tailoring types that alternate methodologies cannot detect. For instance, individual interviews with older adults identified trust issues surrounding tailored information. Specifically, older adults distrustful of tailored information expressed a desire for information that informed the basis of tailored information. This finding suggests a relationship may exist between trust, transparency, and dose that could influence tailored interventions. Obtaining such insights, which made valuable contributions to the findings, is only possible through method collecting qualitative data.

Also, the sequential approach to the mixed methods design used in this study provided an additional methodological strength. During data collection, a sequential mixed method approach uses one method prior to another method, rather than using multiple methods to collect data simultaneously (Doorenbos, 2014). In this study, the content analysis confirmed that mFIT V1 could evaluate and quantify the tailoring type and dose provided by diabetes self-management apps. After confirming mFIT's ability to evaluate apps, the subsequent qualitative data collected during the study enabled older adults and developers to provide their perspective on the framework, which informed the subsequent versions of mFIT.

SUMMARY

In this chapter I discussed the findings for the mFIT framework, along with technology-based approaches to self-management and age-related self-management challenges. First, I discussed the different purposes mFIT serves, and the ways mFIT facilitates key stakeholders, such as older adults with diabetes, mobile app developers, and researchers. Second, I presented the theoretical implications of mFIT, and present an updated message effects model that builds on the original model. Third, I discussed the findings in the context of technology-based approaches to diabetes self-management. Fourth, I discussed the way the findings inform age-related challenges to diabetes self-management, specifically examining the way tailoring may help address the cognitive and sensory changes that occur with age.

STUDY LIMITATIONS AND FUTURE DIRECTIONS

This study contains limitations. First, this study used a convenience sample for older adult diabetics recruited through diabetes self-management courses offered at YMCAs and senior centers located in Texas and California. As a result, this sample may not represent the older adult diabetic population, as this sample possessed sufficient health and interest to attend self-management classes. Similarly, this study used a convenience sample for mobile app developers recruited by contacting app developers listed on Google Apps through email.

Future directions for this research include further investigating and developing the mFIT framework. A key goal in developing the mFIT framework involves identifying the mechanisms that support tailoring. Consistent with this goal, and the goal of improving chronic condition self-management among older adults, I will develop tailored chronic condition self-management interventions for older adults delivered with mobile apps. These theory-based interventions will use the mFIT framework for guidance and can help identify tailoring's mechanisms. Additionally, future studies should identify the inter-rater reliability of the mFIT framework. Also, a revised evaluation form could be developed that expands on the dichotomous yes/no response items from the current form. These items can be assessed in future iterations of mFIT using a Likert scale or similar interval-level measure. Further, large-scale, randomized controlled trials can provide a strong empirical base for this research. To support this research, I plan to seek federal funding from agencies like NIH, targeting funding opportunities such as self-management for health in chronic conditions (PA-18-384) and mHealth Tools for Individuals with Chronic Conditions to Promote Effective Patient-Provider Communication, Adherence to Treatment and Self-Management (PA-18-386).

Appendix A: Senior Center Commitment Letter

Mastick Senior Center
1155 Santa Clara Avenue, Alameda, California 94501 (510) 747-7500

September 13, 2016

Dr. James Wilson, Ph.D.
Chair, Institutional Review Board
P.O. Box 7426
Austin, TX 78713
irbchair@austin.utexas.edu

Dear Dr. Wilson:

This letter grants Ivan Watkins, a PhD candidate at the University of Texas at Austin, permission to conduct research at the Mastick Senior Center. The project, titled "Developing a framework to evaluate the types and dose of tailored information in mobile apps for chronic condition self-management" will involve:

- Focus group sessions in a room provided by the senior center with approximately 15-20 participants. These sessions will center on understanding older adults' use of mobile apps to self-manage their diabetes.
- Individual interviews with five participants to be held at the senior center. These interviews will also focus on understanding older adults' use of mobile apps to self-manage their diabetes.

The Mastick Senior Center is a publicly-funded senior center that provides a well-rounded selection of programs and services for health, education, and recreation to over 150,000 older adult visitors per year. Activities include computer classes, book clubs, bingo, yoga, and day trips. The Mastick Senior Center was selected for this project because of its excellent reputation for enriching older adults' lives through its programming, along with the ability to provide space and access to wireless internet.

Please do not hesitate to contact me should you have any question or need other information.

Sincerely,

Jackie Krause
Recreation Manager
Alameda Recreation and Parks/Mastick Senior Center
1155 Santa Clara Avenue
Alameda, CA 94501

Appendix B: Older Adult Interview Questions

Survey question 1: Describe any apps that you have used to help manage your diabetes.

Interview questions:

1) *What types of tailored information did this app provide, if any?*

2) *What benefits or challenges did this tailored information present for you?*

3) *What features of this app did you find helped you manage your diabetes, if any?*

Survey question 2: Which tailoring types do you believe could best support or facilitate you in managing your diabetes? Please explain your reasoning.

Interview questions:

1) *Similarly, are there any tailoring types that you believe would not support you in self-managing diabetes? Explain your reasoning.*

2) *Are there any tailoring types you find supportive that do not appear in the framework?*

Survey question 3: What edits would you make to the framework? This could include adding, removing, combining, renaming, redefining or dividing elements.

Interview questions:

1) *Please describe your rationale for the suggested edits. For instance, you may want to add a tailoring type to the framework because you find that tailoring type useful.*

2) *What types of edits would you make to the language used in the framework? For instance, is the language overly complex or simplistic?*

Survey question 4: What additional suggestions for the framework do you have?

Interview questions:

1) *Please explain your rational for these additional suggestions.*

2) *Are there any other issues, questions, or comments surrounding the mFIT framework that you might have?*

Appendix C: App Developers Interview Questions

Survey question 1: Please describe any apps you use or designed that incorporate tailoring.

Interview questions:

1) What function did the tailored information serve for the app?

2) *Describe the type of tailored information the app provided. Do not restrict yourself to the categories included in the framework.*

3) *Did the tailored information accomplish it's purpose for the app? Describe why or why not.*

Survey question 2: Which tailoring types do you believe could best support or facilitate users managing a chronic condition? Please explain your reasoning.

Interview questions:

1) *Which types of tailoring do you believe would not support or facilitate users managing a chronic condition, such as diabetes. Please explain your reasoning.*

2) *If you are unsure which types of tailoring might best support users managing a chronic condition, are there any other contexts these tailoring types would be useful?*

Survey question 3: What edits would you make to the framework? This could include adding, removing, combining, renaming, redefining or dividing the elements and examples.

Follow-up questions:

1) *Please describe the rationale for the suggested edits. For instance, you might remove a tailoring type from the framework because you don't believe it is useful or relevant to self-managing diabetes.*

2) *What types of edits would you make to the language used in the framework? For instance, you might find the language too technical or simplistic to effectively describe a tailoring type.*

Survey question 4: What additional suggestions for the framework do you have?

Follow-up questions:

1) *Please explain your rational for these additional suggestions.*

2) *Are there any other issues, questions, or comments surrounding the mFIT framework that you might have?*

Appendix D: Institutional Review Board Approval Letter

OFFICE OF RESEARCH SUPPORT

THE UNIVERSITY OF TEXAS AT AUSTIN

P.O. Box 7426, Austin, Texas 78713 · Mail Code A3200
(512) 471-8871 · FAX (512) 471-8873

FWA # 00002030

Date: 05/12/17

PI: Ivan Watkins II

Dept: Information, School of

Title: Mobile Apps for Chronic Condition Self-Management among Older Adults

Re: IRB Expedited Approval for Protocol Number 2017-04-0030

Dear Ivan Watkins II:

In accordance with the Federal Regulations the Institutional Review Board (IRB) reviewed the above referenced research study and found it met the requirements for approval under the Expedited category noted below for the following period of time: 05/12/2017 to 05/11/2018. *Expires 12 a.m. [midnight] of this date.* If the research will be conducted at more than one site, you may initiate research at any site from which you have a letter granting you permission to conduct the research. You should retain a copy of the letter in your files.

Expedited category of approval:

☐ 1) Clinical studies of drugs and medical devices only when condition (a) or (b) is met. (a) Research on drugs for which an investigational new drug application (21 CFR Part 312) is not required. (Note: Research on marketed drugs that significantly increases the risks or decreases the acceptability of the risks associated with the use of the product is not eligible for expedited review). (b) Research on medical devices for which (i) an investigational device exemption application (21 CFR Part 812) is not required; or (ii) the medical device is cleared/approved for marketing and the medical device is being used in accordance with its cleared/approved labeling.

☐ 2) Collection of blood samples by finger stick, heel stick, ear stick, or venipuncture as follows: (a) from healthy, non-pregnant adults who weigh at least 110 pounds. For these subjects, the amounts drawn may not exceed 550 ml in an 8 week period and collection may not occur more frequently than 2 times per week; or (b) from other adults and children2, considering the age, weight, and health of the subjects, the collection procedure, the amount of blood to be collected, and the frequency with which it will be collected. For these subjects, the amount drawn may not exceed the lesser of 50 ml or 3 ml per kg in an 8 week period and collection may not occur more frequently than 2 times per week.

☐ 3) Prospective collection of biological specimens for research purposes by non-invasive means. Examples:
- (a) Hair and nail clippings in a non-disfiguring manner.
- (b) Deciduous teeth at time of exfoliation or if routine patient care indicates a need for extraction;
- (c) Permanent teeth if routine patient care indicates a need for extraction.

OFFICE OF RESEARCH SUPPORT

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☐ 1) Clinical studies of drugs and medical devices only when condition (a) or (b) is met. (a) Research on drugs for which an investigational new drug application (21 CFR Part 312) is not required. (Note: Research on marketed drugs that significantly increases the risks or decreases the acceptability of the risks associated with the use of the product is not eligible for expedited review). (b) Research on medical devices for which (i) an investigational device exemption application (21 CFR Part 812) is not required; or (ii) the medical device is cleared/approved for marketing and the medical device is being used in accordance with its cleared/approved labeling.

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☐ 3) Prospective collection of biological specimens for research purposes by non-invasive means. Examples:
  (a) Hair and nail clippings in a non-disfiguring manner.
  (b) Deciduous teeth at time of exfoliation or if routine patient care indicates a need for extraction;
  (c) Permanent teeth if routine patient care indicates a need for extraction.

Appendix E: Initial Set of Diabetes Self-Management Apps

App	Rationale
20 Minute Beginners Workout	Excluded - no diabetes focus
20 Minute Workouts Free: Power 20	Excluded - no self-management focus
20 Minute Workouts Free: Power 20	Excluded - not free
20 Minute Workouts Free: Power 20	Excluded - no diabetes focus
2015 American Diabetes Association	Excluded - no self-management focus
7 Minute Chi - Moving Meditation	Excluded - no diabetes focus
7min Workouts Free - Intense!	Excluded - no self-management focus
AAA+ Diabetes Digest	Excluded - no interactive features
America Association of Diabetes Educators 17	Excluded - no self-management focus
American Associaton of Diabetes Educators 16	Excluded - no self-management focus
American Diabetes Association Advocacy	Excluded - no self-management focus
American Diabetes Association Standards of Care	Excluded - no self-management focus
Apollo Diabetes Predictor	Excluded - no self-management focus
Best Diabetes Control Lite	Included in final sample
CalorieKing Food Search	Excluded - no diabetes focus
Carbs & Cals: Visual counter for diet & diabetes	Excluded - not free

CarbsControl	Excluded - not free
CardioVisual - Heart App	Excluded –no diabetes focus
Certified Diabetes Educator Exam Prep 2017	Excluded - no self-management focus
Contour Diabetes App	Included in final sample
Diabetes	Included in final sample
Daily Carb for iPad - Glucose Control and Tracker	Included in final sample
Diabetes ABCs	Excluded - no self-management focus
Diabetes Aid: Brought to you by KFH	Included in final sample
Diabetes App - blood sugar control, glucose tracker and carb counter	Excluded - not free
Diabetes App Lite	Included in final sample
Diabetes Connection	Excluded - no self-management focus
Diabetes CookBook	Excluded - not free
Diabetes Cookbook + Lite	Excluded - not free
Diabetes Cravings	Excluded - not free
Diabetes Cure Diet	Excluded - no self-management focus
Diabetes Daily	Excluded - no self-management focus
Diabetes Diagnostics	Excluded - no self-management focus
Diabetes Diet FREE	Excluded - no self-management focus

Diabetes FAQ	Excluded - no self-management focus
Diabetes Forecast	Excluded - no interactive features
Diabetes Forum	Excluded - no self-management focus
Diabetes Glucose Tracker	Excluded - not free
Diabetes Guide - Glucoguide	Included in final sample
Diabetes Health	Excluded - no interactive features
Diabetes Health Magazine	Excluded - no interactive features
Diabetes in Check	Included in final sample
Diabetes Insight	Excluded - no self-management focus
Diabetes Lifelines	Excluded - no self-management focus
Diabetes Mellitus pocket	Excluded - not free
Diabetes Mgr	Included in sample
Diabetes Pilot HD	Excluded - not free
Diabetes Pilot Pro	Included in final sample
Diabetes Recipe App	Excluded - no self-management focus
Diabetes Self-Management	Excluded – no interactive features
Diabetes Support Forum	Excluded - no self-management focus
Diabetes Trivia Quiz	Excluded - no self-management focus

Diabetes: M	Included in final sample
Diabetes@Point of Care	Excluded - no self-management focus
DiabetesConnect	Included in final sample
Diagnosis and Management of Gestational Diabetes	Excluded - not free
Eat Health Hypnosis	Excluded - no diabetes focus
Emergency First Aid	Excluded - no diabetes focus
emojilift Diabetes Extra	Excluded - not free
EZBDS	Included in final sample
Fat Lady Fitness & Burn Fat	Excluded - no diabetes focus
Female Fitness Workouts - Exercise for Women Health	Excluded - no diabetes focus
Food & Drink Carb Counter for Diabetics	Excluded - not free
Food Diary and Calorie Tracker by MyNetDiary	Excluded - not free
GenieMD	Excluded - no diabetes focus
Get Fit with Andrew Johnson	Excluded - not free
Glucose Companion for iPad - Blood sugar tracker	Excluded - not free
Glucose Companion Pro for iPad	Included in final sample
Glucose Monitor	Included in final sample
Glucose Wiz - Blood Sugar Log & Medication	Excluded - not free
Glucose Wiz Pro	Excluded - not free
Glycemic Index & Load of food for low carb diet	Included in final sample
GoMeals	Included in final sample

I Got This: An Interactive Story	Excluded - no self-management focus
iDiabetes care bundle	Excluded - not free
Learn Diabetes, Cancer, and Nutrition	Excluded - no self-management focus
Low Carb Diet Tracker PRO	Excluded - not free
Medical Toolbox	Excluded - not free
Mumoactive	Included in final sample
My Action Planner	Excluded - not free
mySugr Diabetes Training: 10 Fun Type 2 Academy Video Tips for Diabetics	Excluded - not free
Nightscout	Excluded - no self-management focus
Nutrients - Nutrition facts for foods and recipes	Excluded - no diabetes focus
OneTouch Reveal	Excluded - no Self-management focus
Pet Diabetes Tracker	Excluded - no self-management focus
Photo Step by Step - Easy and Healthy Mediterranean Food Recipes for Every Occasion	Excluded - not free
PredictBGL Diabetes Manager, Insulin Doses	Included in final sample
Pregnancy & Beyond Workout Kit	Excluded - not free
Pregnant with Diabetes	Excluded - no self-management focus
Prognosis : Diabetes	Excluded - no self-management focus

Recipes for Diabetes	Excluded - no self-management focus
Relax with Andrew Johnson	Excluded - not free
Sugarmate	Excluded - no self-management focus
t:simulator App	Excluded - no self-management focus
Taste My Recipes	Excluded - no diabetes focus
The Low-Glycal Diet - Healthy Weight Loss Tracker	Excluded - not free
Vida Health Coach - Lose Weight & Manage Conditions	Excluded - no self-management focus
Well Being Journal	Excluded - no interactive features
Your Diabetes Diary	Included in final sample
Zinio - The World's Magazine Newstand	Excluded - no interactive features

Appendix F: Definitions of Diabetes Self-Management Activities

Activity	*Definition*
Diet	Activities include counting carbohydrates, reading food labels, measuring the amount of a serving, developing a practical meal plan, preventing high or low blood sugar, and setting goals for healthy eating.
Physical activity	Activities that gets [individuals] moving and helps them stay healthy. It may include resistance training, e.g., activities that help you build muscle and train, or cardio, which is exercise that raises your heart rate.
Blood Glucose Monitoring	Checking your blood levels regularly to ensure they are on target.
Medication	Medication may include pills that lower individuals' blood sugar, aspirin, blood pressure medication, cholesterol-lowering medication, or other medications to reduce the risk of complications and improve individuals' well-being.
Problem solving	Skills for problem solving include learning how to recognize and react to high and low blood sugar levels and learning how to manage on days when you are sick.

Healthy coping	Approaches to coping with stress include being active, participating in faith-based activities or meditating, pursuing hobbies, or attending support groups.
Risk reduction	Taking steps to reduce the risk of complications, such as not smoking, regularly visiting the doctor, visiting the eye doctor once per year, going to the dentist, caring for the feet, and listening to your body.

Appendix G: Set of Diabetes Self-Management Apps

App Name	*Developer*	*Last Update*
Diabetes App Lite	BHI Technologies, Inc.	November 14, 2013
Diabetes in Check	Everyday Health, Inc.	November 14, 2016
DiabetesConnect	SquareMed Software	June 21, 2015
Glucose Companion	Maxwell Software	October 11, 2016
Diabetes Pilot Pro	Digital Altitudes, LLC	December 20, 2016
Glucose Monitor	Taconic System LLC	November 21, 2015
PredictBGL Diabetes Manager	Datamystic PTY LTD	November 23, 2016
Diabetes Aid	Saleh Almusallam	March 18, 2013
Diabetes: M	Sirma Medical Systems AD	November 20, 2016
Contour Diabetes App	Ascensia Diabetes Care US Inc.	December 28, 2016
Glycemic Index	Rafal Platek	October 20, 2016
Best Diabetes Control Lite	Galia Aviram	June 21, 2013
Diabetes Mgr	Cary Mariash	April 5, 2017
D-Life Diabetes	GiveEasy Pty Limited	November 10, 2015
Daily Carb for iPad	Maxwell Software	October 9, 2016
Diabetes Guide – Glucoguide	GlucoGuide Corp	December 20, 2016
Your Diabetes Diary	MacHealth Pty Ltd	January 25, 2013
EZBDS	EZBDS, LLC	July 24, 2015

GoMeals	Sanofi-Aventis Groupe	December 13, 2016
Mumoactive	Strategic Specific Ltd.	January 12, 2016

Appendix I: Introductory Email

"Dear [participant name],

Thank you for agreeing to participate in this study. My name is Ivan Watkins and I am a PhD candidate at the School of Information at The University of Texas at Austin. Before we begin, take a moment to review the cover letter attached with this email. This cover letter provides some background information for this study, and outlines the study activities. Please let me know if you have questions about the cover letter or any other aspect of the study.

Next, please complete the survey questionnaire, also attached with this email. Feel free to contact me should you have any questions about this survey. After you complete the survey, please email it to: iwatkins@utexas.edu

Once you return the completed survey, we will begin the interview portion of the study during which I will ask some follow-up questions based on your responses to the survey.

Thank you,
Ivan Watkins
Ph.D. Candidate
PH: 510-735-4300
Email: iwatkins@utexas.edu

Appendix J: Questionnaire for Mobile Application Developers

Part 1: Background

1. **Age: ________________**

2. **Gender:** 1 Female 2 Male

3. **What is your highest level of education?**
   1 No formal education

   2 Less than high school graduate

   3 High school graduate/GED

   4 Vocational training

   5 Some college/Associate's degree

   6 Bachelor's degree (BA, BS)

   7 Master's degree (or other post-graduate training)

   8 Doctoral degree (PhD, MD, EdD, DDS, JD, etc.)

4. **Do you consider yourself Hispanic or Latino?** 1 Yes 2 No

5. **How would you describe your primary racial group?**
   1 American Indian/Alaska Native

   2 Asian

   3 Black/African American

   4 Multi-racial

   5 Native Hawaiian/Pacific Islander

   6 White Caucasian

   7 Other________________

6. **How long have you been working with mobile application design?**
   1 Never

   2 Less than one year (< 1 year)

   3 More than one year, less than three years (1-3 years)

4 More than three years, less than five years (3-5 years)

5 More than five years (> 5 years)

Part 2: Tailoring Framework

Apps help people manage chronic health conditions, such as diabetes. For example, an app may warn users about high blood sugar. Likewise, apps can provide **tailored information**.

Tailored information is defined as: *information developed for an individual, related to an outcome of interest, based on an individual assessment*.

Different types of tailored information exist. The framework below defines these types and includes examples:

Tailoring Type	*Definition*	*Example*
Personalization	A message stating it is designed for an individual.	"We designed this message for you based on your weight."
Contextualization	Messages placed in a cultural context.	"Don't eat too much at Christmas dinner"
Descriptive feedback	Messages presenting raw data about the user.	"You weigh 175 pounds."
Evaluative feedback	Feedback interpreting raw data.	"Your weight is unhealthy."
Content-matching	Messages tailored for health behavior change theories.	"You can lose weight!"
Dose	Tailoring the amount, frequency, sequence, and delivery system used to provide tailored information.	An app sends a message each hour.
Event-triggered information	The app tailors information in response to an event.	"Thank you for recording your weight, you still weight too much."

The following questions refer to tailoring and this framework

1. Please describe any apps you use or designed that incorporate tailoring:

2. Which tailoring types do you believe could best support or facilitate users managing a chronic condition? Please explain your reasoning.

3. What edits would you make to the framework? This could include adding, removing, combining, renaming, redefining or dividing elements.

4. What additional suggestions for the framework do you have?

Thank you for completing this survey questionnaire!

Please email a completed copy of the survey to: **iwatkins@utexas.edu**

Appendix K: Questionnaire for Older Adults

Part 1: Background Questionnaire

1. **Age: ________________**

2. **Gender:** 1 Female 2 Male

3. **What is your highest level of education?**
   1 No formal education

   2 Less than high school graduate

   3 High school graduate/GED

   4 Vocational training

   5 Some college/Associate's degree

   6 Bachelor's degree (BA, BS)

   7 Master's degree (or other post-graduate training)

   8 Doctoral degree (PhD, MD, EdD, DDS, JD, etc.)

4. **In general, would you say your health is:**

1	2	3	4	5
Poor	Fair	Good	Very Good	Excellent

5. **Do you consider yourself Hispanic or Latino?** 1 Yes 2 No

6. **How would you describe your primary racial group?**
   1 American Indian/Alaska Native

   2 Asian

   3 Black/African American

   4 Multi-racial

   5 Native Hawaiian/Pacific Islander

   6 White Caucasian

   7 Other_______________

7. **Is English your primary language?** 1 Yes 2 No

8. **How many years of experience do you have using mobile applications?**
   1 Never

   2 Less than one year (< 1 year)

   3 More than one year, less than three years (1-3 years)

   4 More than three years, less than five years (3-5 years)

   5 More than five years, less than ten years (5-10 years)

   6 More than ten years (>10 years)

9. **How often do you use a mobile application?**

   1 Never

   2 Less than once a month

   3 More than once a month

   4 Once a week

   5 Every 2-3 days

   6 Every day

Part 2: Tailoring Framework

Apps can help people manage chronic health conditions, such as diabetes. For example, an app may warn users of their high blood sugar. Likewise, apps can provide **tailored information**.

Tailored information is: *information developed for an individual, related to an outcome of interest, based on an individual assessment*.

Different types of tailored information exist. The framework below defines these types:

Tailoring Type	*Definition*	*Example*
Personalization	A message stating it is designed for an individual.	"We designed this message for you based on your weight."
Contextualization	Messages placed in a cultural context.	"Don't eat too much at Christmas dinner"

Descriptive feedback	Messages presenting raw data about the user.	“You weigh 175 pounds.”
Evaluative feedback	Feedback interpreting raw data.	“Your weight is unhealthy.”
Content-matching	Messages tailored for health behavior change theories.	“You can lose weight!”
Dose	Tailoring the amount, frequency, sequence, and delivery system used to provide tailored information.	An app sends a message each hour.
Event-triggered information	The app tailors information in response to an event.	“Thank you for recording your weight, you still weight too much.”

Instructions: *Please consider this framework in answering the following questions:*

1. Please describe any apps that you have used to help manage your chronic conditions, such as diabetes.

2. Which tailoring types do you believe can best support or facilitate you in managing your chronic conditions, such as diabetes? Please explain your reasoning.

3. What changes would you make to the framework? This could include adding, removing, combining, renaming, redefining or dividing elements.

4. What additional suggestions for the framework do you have?

Thank you for completing this survey questionnaire! Please email a completed copy of the survey to: iwatkins@utexas.edu.

Appendix L: Spanish Version of Questionnaire for Older Adults

Fecha:____________________

Por favor responda a las preguntas siguientes. Todas sus respuestas son confidénciales. Cualquier documento con sus respuestas no incluirá su nombre o su información. Muchísimas gracias por su tiempo y ayuda.

Parte 1: Encuesta Demográfica

1. **Edad: _______________**

2. **Género:** 1 Hembra 2 Varón

3. **¿Cuál es su nivel de educación?**

   1 No educación formal

   2 Menos que escuela secundaria

   3 Graduado de escuela secundaria

   4 Escuela vocacional

   5 Alguna educación superior

   6 Graduado de educación superior

   7 La maestría

   8 El doctorado (PhD, MD, EdD, DDS, JD)

4. **En general, mi salud es:**

1	2	3	4	5
Mal	Pasable	Bueno	Muy Bueno	Excelente

5. **¿Usted es Hispano o Latino?** 1 Sí 2 No

6. ¿Cuál es tu principal grupo racial?

1 El Nativo Americano/El Nativo de Alaska

2 Asiático

3 Afroamericano

4 Multi-racial

5 El Hawaiano/Isleño del Pacífico

6 Blanco/Caucásico

7 Otro grupo_______________

7. ¿Es inglés su primera lengua? 1 Sí 2 No

8. ¿Cuantos años de experiencia tienes con aplicaciones móviles?

1 Menos de un año (< 1 año)

2 Más de un año, menos de tres años (1-3 años)

3 Más de tres años, menos de cinco años (3-5 años)

4 Más de cinco años, menos de diez años (5-10 años)

5 Más de diez años (>10 años)

Parte 2: El Marco de Personalización

Aplicaciones móviles ayudan a manejar enfermedades crónicas, como la diabetes. Por ejemplo, una aplicación móvil puede advertir a sus usuarios sobre su alto nivel de azúcar en la sangre. Igualmente, las aplicaciones pueden proporcionar **información personalizada**.

Información personalizada es: información desarrollada para individuos, relacionada con un resultado de interés, basada en una evaluación individual.

Existen diferentes tipos de información personalizada. El marco abajo define esto tipos:

Tipo	*Definición*	*Ejemplo*

Personalización	Un mensaje que es diseñado para un individuo.	"Diseñamos este mensaje para usted basado en su peso"
Contextualización	Mensajes colocados en un contexto cultural.	"No comas demasiado en la cena de Navidad"
Comentario Descriptivos	Mensajes que presentan información sin procesar sobre el usuario.	"Usted pesa 175 libras."
Comentario Evaluativos	Comentarios interpretando los datos sin procesar.	"Su peso no es saludable.
Contenido a juego	Mensajes personalizados para teorías de cambio de comportamiento de salud.	"Usted puede perder peso!"
La dosis	Personalizar la cantidad, frecuencia, secuencia y el sistema de entrega utilizado para proporcionar información personalizada.	"Una aplicación envía un mensaje cada hora."
Información activada por un evento	La aplicación personaliza información en respuesta a un evento.	"Gracias por registrar tu peso, todavía pesas demasiado"

Instrucciones: *Por favor considere este marco cuando conteste las preguntas siguientes:*

9. Describa cualquier aplicaciones móviles que usted ha usado para manejar su diabetes:

10. ¿Qué tipo de personalización cree que podría apoyar o facilitar su manejo de la diabetes? Por favor explique su razonamiento:

11. ¿Qué cambios harías al marco? Esto puede incluir agregar, eliminar, combinar, renombrar, redefinir o dividir elementos.

12. ¿Qué sugerencias adicionales tiene para el marco?

¡Muchísimas gracias por completar este cuestionario de encuesta! Envíe por correo electrónico una copia completa de la encuesta a: iwatkins@utexas.edu.

Appendix M: Spanish Version of Cover Letter

SOLO PARA USO DE IRB
Número de Investigación: 2017-04-0030
Fecha de Aprobación: 08/28/2018
Fecha de Vencimiento: 05/31/2019

Título: Aplicaciones móviles para el autocontrol de condiciones crónicas entre adultos mayores.

Introducción:

El propósito de este formulario es proporcionarle información que puede afectar su decisión sobre si participa o no en este estudio de investigación. La persona que realiza la investigación responderá a cualquiera de sus preguntas. Lea la información abajo y pregunta cualquier pregunta que tenga antes de decidir si participa o no.

Propósito del Estudio:

Se le ha pedido que participe en un estudio de investigación sobre el uso de información adaptada de las personas mayores en las aplicaciones móviles para auto controlar las enfermedades crónicas. El propósito de este estudio es desarrollar un marco para evaluar la información personalizada proporcionada por aplicaciones de autocontrol de enfermedades crónicas basadas en mHealth para adultos mayores. En este estudio, la diabetes ejemplificará una afección crónica. Lo invitamos a participar en este estudio porque es diabético y tiene al menos 65 años de edad.

¿Qué se te pedirá que hagas?

Si acepta participar en este estudio, se le pedirá que:

- Participe en una entrevista individual
- Complete un breve cuestionario sobre información demográfica, como su edad, junto con preguntas abiertas sobre información personalizada.
- Este estudio incluirá aproximadamente 10 participantes ancianos. El proyecto comenzará en diciembre de 2018 y continuará durante un mes.
- No habrá grabación de audio o video.

¿Cuáles son los riesgos involucrados en el estudio?

No hay riesgos previsibles para participar en este estudio. El riesgo de participar en el estudio no difiere de los riesgos de la vida cotidiana.

¿Cuáles son los posibles beneficios involucrados en estudio?

Los resultados de este proyecto de investigación pueden aumentar nuestro conocimiento sobre el uso de aplicaciones de autocontrol de enfermedades crónicas en adultos mayores que brindan información personalizada, junto con los desafíos y mecanismos que respaldan a las personas mayores que usan estas aplicaciones. Este conocimiento podría conducir a intervenciones de autocontrol de afecciones crónicas basadas en aplicaciones móviles a medida más efectivas para adultos mayores.

¿Tienes que participar?

No, tu participación es voluntaria. Puede decidir no participar o, si comienza el estudio, puede retirarse en cualquier momento. Retirar o rehusarse a participar no afectará su relación con la Universidad de Texas en Austin (Universidad) o el centro de personas mayores en cualquier manera.

¿Habrá alguna compensación?

Recibirás una tarjeta de regalo Target de $ 20 por su participación. Los pagos se realizarán al final de la sesión del grupo de enfoque, después de completar la sesión. Usted será responsable de los impuestos calculados sobre la compensación.

¿Cómo se protegerá su privacidad y confidencialidad si participa en este estudio de investigación?

Este estudio es confidencial y su participación en la investigación es voluntaria. Para garantizar que su información se mantenga confidencial y privada: 1) los formularios del cuestionario de la encuesta y los datos recopilados adicionales se archivarán de manera segura en un archivador en la oficina del investigador; 2) se usará un código para identificar a los participantes en los formularios del cuestionario de la encuesta y cualquier otro dato recopilado; 3) mediante el uso de una clave de identificación, el investigador puede vincular el cuestionario de la encuesta a su identidad; 4) solo el investigador tendrá acceso a esta clave de identificación. Después de que finalice este estudio, se destruirá esta clave de identificación para garantizar que su información se mantenga privada y confidencial.

Si es necesario que la Instituional Review Board revise los registros del estudio, la información que pueda vincularse con usted estará protegida en la medida permitida por la ley. Sus registros de investigación no se divulgarán sin su consentimiento a menos que así lo exija la ley o una orden judicial. Los datos resultantes de su participación pueden ponerse a disposición de otros investigadores en el futuro con fines de investigación no detallados en este formulario de consentimiento. En estos casos, los datos no contendrán información que pueda asociarlo con usted o con su participación en cualquier estudio.

¿A quién contactar con preguntas sobre el estudio?

Antes, durante o después de su participación, puede comunicarse con el investigador Ivan Watkins al (510)-735-4300 o enviar un correo electrónico a iwatkins@utexas.edu si tiene alguna pregunta o si cree que ha sido perjudicado.

¿A quién contactar con preguntas sobre sus derechos como participante en la investigación?

Para preguntas sobre sus derechos o cualquier insatisfacción con cualquier parte de este estudio, puede comunicarse, anónimamente si lo desea, con la Junta de Revisión Institucional por teléfono al (512) 471-8871 o por correo electrónico a orsc@uts.cc.utexas.edu.

References

Abrams, D. B., Mills, S., & Bulger, D. (1999). Challenges and future directions for tailored communication research. *Annals of Behavioral Medicine, 21*(4), 299-306.

Administration on Aging. (2013). *A profile of older Americans: 2012*. Retrieved from http://www.aoa.gov/Aging_Statistics/Profile/2012/docs/2012profile.pdf

Aikens, J. E., Zivin, K., Trivedi, R., & Piette, J. D. (2014). Diabetes self-management support using mHealth and enhanced informal caregiving. *Journal of Diabetes and its Complications, 28*(2), 171-176. doi:10.1016j.jdiacomp.2013.11.008

Ajzen, I. (1985). *From intentions to actions: A theory of planned behavior*.

American Association of Diabetes Educators. (2018). AADE7 Self-care behaviors. Retrieved from https://www.diabeteseducator.org/living-with-diabetes/aade7-self-care-behaviors

American Diabetes Association. (2014). Standard of medical care in diabetes - 2014. *Diabetes Care, 37*(Suppl. 1), S14-S80. doi:10.2337/dc14-S014

American Diabetes Association. (2015). Foundations of care: Education, nutrition, physical activity, smoking cessation, psychosocial care, and immunization *Diabetes Care, 38*(Suppl 1).

Anderson, M. & Perrin, A. (2017). Tech adoption climbs among older adults. *Pew Research Center*.

Antypas, K., & Wangberg, S. C. (2014). An Internet- and mobile-based tailored intervention to enhance maintenance of physical activity after cardiac rehabilitation: Short-term results of a randomized controlled trial. *Journal of Medical Interent Research, 16*(3), e77. doi:10.2196/jmir.3132

Arnhold, M., Quade, M., & Kirch, W. (2014). Mobile applications for diabetics: A systematic review and expert-based usability evaluation considering the special requirements of diabetes patients age 50 and above. *Journal of Medical Interent Research, 16*(4), e104. doi:10.2196/jmir.2968

Ayers, S., Baum, A., McManus, C., Newman, S., Wallston, K., Weinman, J., & West, R. (Eds.). (1997). *The health belief model* (Second ed.). Camrbidge, England.

Baek, R. N., Tanenbaum, M. L., & Gonzalez, J. S. (2014). Diabetes burden and diabetes distress: The buggering effect of social support. *Annals of Behavioral Medicine, 48*(145-155). doi:10.1007/s12160-013-9585-4

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *Psychological review, 84*(2), 191.

Bandura, A. (1998). Health promotion from the perspective of social cognitive theory. *Psychology and Health, 13*, 623-649.

Bandura, A. (2004). Health promotion by social cognitive means. *Health Education & Behavior, 31*(2), 143-164.

Baumeister, R. F., DeWall, C. N., Ciarocco, N. J., & Twenge, J. M. (2005). Social exclusion impairs self-regulation. *Journal of Personality and Social Psychology, 88*(4), 589-604.

Bawden, D., & Robinson, L. (2009). The dark side of information: Overload, anxiety and other paradoxes and pathologies. *Journal of Information Science, 35*(2), 180-191. doi:10.1177/0165551508095781

Bellg, A. J., Borrelli, B., Resnick, B., Hecht, J., Minicucci, D. S., Ory, M., . . . Czajkowski, S. (2004). Enhancing treatment fidelity in health behavior change studies: Best practices and recommendations from the NIH behavior change consortium. *Health psychology, 23*(5), 443-451. doi:10.1037/0278-6133.23.5.443

Bodenheimer, T., & Pham, H. (2010). Primary care: Current problems and proposed solutions. *Health Affairs, 29*(5), 799-805.

Bordier, L., Doucet, J., Boudet, J., & Bauduceau, B. (2014). Update on cognitive decline and dementia in elderly patients with diabetes. *Diabetes & Metabolism, 40*(5), 331-337. doi:10.1016/j.diabet.2014.02.002

Borella et al. (2010). Working memory training in older adults: Evidence of transfer and maintenance efforts. *Psychology and Aging*, *24*(4), 767-778.

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology, 3*(2), 77-101. doi:10.1191/1478088706qp063oa

Brehm, S. S., & Brehm, J. W. (1981). *Psychological reactance: A theory of freedom and control*. New York, NY: Academic Press

Brown, S. A., Dougherty, J. R., Garcia, A., Kouzekanani, K., & Hanis, C. L. (2002). Culturally competent diabetes self-management education for Mexican Americans: The Starr County Border Health Initiative. *Diabetes Care, 25*(2), 259-268.

Brown, S. A., Garcia, A., Winter, M., Silva, L., Brown, A., & Hanis, C. L. (2011). Integrating education, group support, and case management for diabetic hispanics. *Ethnicity & Disease, 21*(1), 20-26.

Burnette, J. L. (2007). Operationalization. In R. F. Baumeister & K. D. Vohs (Eds.), *Encyclopedia of Social Psychology* (pp. 636-637). Thousand Oaks, CA: SAGE Publications, Inc.

Cacioppo, J. T., & Petty, R. E. (1984). The elboration likelihood model of persuasion. In T. C. Kinnear (Ed.), *Advances in Consumer Research* (Vol. 11, pp. 673-675). Provo, UT: Assofication for Consumer Research.

Cacioppo, J. T., & Petty, R. E. (1989). Effects of message repetition on argument processing, recall, and persuasion. *Basic and Applied Social Psychology, 10*, 3-12.

Cahana-Amitay, D., Albert, M. L., Ojo, E. A., Sayers, J., Goral, M., Obler, L. K., & Spiro, A. (2013). Effects of hypertension and diabetes on sentence comprehension in aging. *The Journals of Gerontology Series B, 68*(4), 513-521.

Center for Disease Control and Prevention. (2012). Diabetes Public Health Resource. Retrieved from http://www.cdc.gov/diabetes/statistics/mobility/health_status/fig3.htm

Center for Disease Control and Prevention. (2013). *The state of aging and health in America 2013*. Atlanta, GA: Centers for Disease Control and Prevention, US Department of Health and Human Services.

Centers for Disease Control and Prevention. (2013). *Arthritis and diabetes*. Retrieved from http://www.cdc.gov/arthritis/data_statistics/comorbidities-diabetes.htm

Centers for Disease Control and Prevention (2017). National Diabetes Statistics Reports. Retrieved from https://www.cdc.gov/diabetes/pdfs/data/statistics/national-diabetes-statistics-report.pdf

Chan, C., & Kaufman, D. R. (2011). A framework for characterizing eHealth literacy demands and barriers. *Journal of Medical Interent Research, 13*(4), e94.

Chen, X., Hay, L., Waters, E., Kiviniemi, M., Biddle, C., & Schofield. (2018). Health literacy and use and trust in health information. *Journal of Health Communication*, *23*(8).

Choi, S. E., & Rush, E. B. (2012). Effect of a short-duration culturally tailored community-based diabetes self-management intervention for Korean immigrans: A pilot study. *Diabetes Educator, 38*(3), 377-385. doi:10.1177/0145721712443292.

Chomutare, T., Fernandez-Luque, L., Ardand, E., & Hartvigsen, G. (2011). Feature of mobile diabetes applications: Review of the literature and analysis of current applications compared against evidence-based guidelines. *Journal of Medical Interent Research, 13*(3), e65.

Chrvala, C. A., Sherr, D., & Lipman, R. D. (2015). Diabetes self-management education for adults with type 2 diabetes mellitus: A systematic review of the effect on glycemic control. *Patient education and counseling, 15*.

Cornwell, E. Y., & Waite, L. J. (2009). Social disconnectedness, perceived isolation, and health among older adults. *Journal of Health and Social Behavior, 50*(1), 31-48.

Crook, B., Stephens, K. K., Pastorek, A. E., Mackert, M., & Donovan, E. E. (2015). Sharing health information and influencing behavioral intentions: The role of health literacy, information overload, and the Internet in the diffusion of healthy heart information. *Health Communication*, 1-12. doi:10.1080/10410236.2014.936336

Creswell J, Klassen A, Plano Clark V, Smith K. (2001) *Best practices for mixed methods research in the health sciences.* National Institutes of Health.

Cudjoe, T.K.M., Roth, D.L., Szanton, S.L., Wolff, J.L., Boyd, C.M., & Thorpe, R.J. (2018). The epidemiology of social isolation: National health & aging trends study. *The Journals of Gerontology: Series B*. doi: 10.1093/geronb/gby037

Dabbs, A. D., Song, M. K., Hawkins, R., Aubrecht, J., Kovach, K., Terhorst, L., . . . Callan, J. (2011). An intervention fidelity framework for technology-based behavioral interventions. *Nursing research, 60*(5), 340-347. doi:doi:10.1097/NNR.0b013e31822cc87d.

David, P., Henry, A., Srivastava, J., Orcena, J., & Thrush, J. (2012). Reactance to a tailored muitimedia intervention encouraging teachers to promote cover-the-cough. *Journal of Health Communication, 17*, 915-928.

De Galan, B. E., Zoungas, S., Chalmers, K., Anderson, C., Dufouil, C., Pillai, A., . . . Woodward, M. (2009). Cognitive function and riks of cardiovascular disease and hypoglycemia in patients with type 2 diabetes: The action in diabetes and vascular disease: Preterax and diamicron modified release controlled evaluation (ADVANCE) trial. *Diabetologia, 52*(11), 2328-2336.

Dennis, C. L. (2003). Peer support within a health care context: A concept analysis. *international Journal of Nursing Studies, 40*, 321-332.

Dennison, L., Morrison, L., Conway, G., & Yardley, L. (2013). Opportunities and challenges for smartphone applications in supporting health behavior change: Qualitative study. *Journal of Medical Interent Research, 15*(4), e86. doi:10.2196/jmir.2583

Dijkstra, A. (2014). The persuasive effects of personalization through name mentioning in a smoking cessation message. *User Modeling and User-Adapted Interaction, 24*(5), 393-411.

DiNapoli, E. A., Wu, B., & Scogin, F. (2014). Social isolation and cognitive function in appalachian older adults *Research on Aging, 36*(2), 161-179. doi:10.1177/0164027512470704

Direito, A., Dale, L. P., Shields, E., Dobson, R., Whittaker, R., & Maddison, R. (2014). Do physical activity and dietary smartphone applications incorporate evidence-based behavior change techniques? *BMC Public Health, 14*. doi:10.1186/1471-2458-14-646

El-Gayar, O., Timsina, P., Nawar, N., & Eid, W. (2013). Mobile applications for diabetes self-management: Status and potential. *Journal of Diabetes Science and Technology, 7*(1).

Eppler, M. J., & Mengis, J. (2004). The concept of information overload: A review of the literature from organization science, accounting, marketing, MIS, and related disciplines. *The Information Society: An International Journal, 20*(5), 325-344. doi:10.1080/01972240490507974

Evers, K., Prochaska, J., Van Marter, D. F., Johnson, J., & Prochaska, J. (2007). Transtheoretical based bullying prevention effectiveness trial in middle schools and high schools. *Educational Research, 49*(4), 397-414.

Floridi, L. (2010). *Information: A very short introduction*. New York, NY: Oxford University Press.

Folstein, M. F., Folstein, S. E., & McHugh, P. R. (1975). A practical method for grading the cognitive state of patients for the clinician. *Journal of Psychiatry Research, 12*, 189-198.

Frenn, M., Malin, S., Brown, R. L., Greer, Y., Fox, J., Greer, J., & Smyczek, S. (2005). Changing the tide: An Internet/video exercise and low-fat diet intervention with middle-school students. *Applied Nursing Research, 18*, 13-21.

Gallagher, K., & Updegraff, J. A. (2012). Health message framing effects on attitudes, intentions, and behavior: A meta-analytic review. *Annals of Behavioral Medicine, 43*(1), 101-116.

Gardner, L., & Leshner, G. (2016). The role of narrative and other-referencing in attenuating psychological reactance to diabetes self-care. *Health Communication, 31*(6), 738-751.

Glanz, K., Rimer, B. K., & Viswanath, K. (2015). *Health behavior and health education: theory, research, and practice*. San Francisco, CA: Jossey-Bass Inc. Publishing.

Goyal, S., & Cafazzo, J. A. (2013). Mobile phone health apps for diabetes management: Current evidence and future developments. *QJM: An International Journal of Medicine, 106*(12), 1067-1069. doi:10.1093/qjmed/hct203

Hall, A. K., Cole-Lewis, H., & Bernhardt, J. M. (2015). Mobile text messaging for health: A systematic review of reviews. *Annual review of public health, 18*(36), 393-415.

Hall, M. G., Sheeran, P., Noar, S. M., Ribisi, K. M., Bach, L. E., & Brewer, N. T. (2016). Reactance to Health Warnings Scale: Development and validation. *Annals of Behavioral Medicine, 50*, 736-750.

Hampton, K., Rainie, L., Lu, W., Shin, I., & Purcell, K. (2015). Social media and the cost of caring. *Pew Internet & American Life Project*.

Harrington, N. G., & Noar, S. M. (2012). Reporting standards for studies of tailored interventions. *Health Education Research, 27*(2), 331-342. doi:10.1093/her/cyr10

Hass, L., Maryniuk, M., Beck, J., Cox, C. E., Duker, P., Edwards, L., . . . Youssef, G. (2012). National standards for diabetes self-management education and support. *Diabetes Care, 35*, 2393-2401.

Hawkins, R. P., Kreuter, M., Resincow, K., Fishbein, M., & Dijkstra, A. (2008). Understanding tailoring in communicating about health. *Health Education Research, 23*(3), 454-466. doi:10.1093/her/cyn004

Hawkley, L. C., Masi, C. M., Berry, J. D., & Cacioppo, J. T. (2006). Loneliness is a unique predictor of age-related differences in systolic blood pressure. *Psychology and aging, 21*(1), 152-164.

Hawkley, L. C., Thisted, R. A., & Cacioppo, J. T. (2009). Loneliness predicts reduced physical activity: Cross-sectional & longitudinal analyses. *Health psychology, 28*(3), 354-363.

Hawkley, L. C., Thisted, R. A., Masi, C. M., & Cacioppo, J. T. (2010). Loneliness predicts increased blood pressure: Five-year cross-lagged analyses in middle-aged and older adults. *Psychology and aging, 25*(1), 132-141. doi:10.1037/a0017805

Henderson, C., Knapp, M., Fernandez, J.L., Beecham, J., Hirani, S.P., Cartwright, M.,… Newman, S. (2013). Cost effectiveness of telehealth for patients with long term conditions (Whole Systems Demonstrator telehealth questionnaire study): Nested economic evaluation in a pragmatic, cluster randomised controlled trial. *British Medical Journal*, *346*.

Huckvale, K., Adomaviciute, S., Prieto, J. T., Leow, M., & Car, J. (2015). Smartphone apps for calculating insulin dose: A systematic assessment. *BMC Medicine, 13*.

Hung, W., Ross, J., Boockvar, K., & Siu, A. (2011). Recent trends in chronic disease, impairment and disability among older adults in the United States. *BMC Geriatrics, 11*(47), 1-12.

Janz, N. K., & Becker, M. H. (1984). The health belief model: A decade later. *Health Education & Behavior, 11*(1), 1-47.

Jiang, J. (2018). Millenials stand out for their technology use, but older generations also embrace digital life. *Pew Internet & American Life Project*.

Johnson, J. D. (2014). Controlling the flood: When more of a dose is less. *Journal of Documentation, 70*(3), 330-345. doi:10.1108/JD-01-2013-0008

Joslin Diabetes Center (2018). Conversion table for blood glucose monitoring. Retreived from: https://www.joslin.org/info/conversion_table_for_blood_glucose_monitoring.html

Kim, A.S.N., Wong-Kee-You, A.M.B., Wiseheart, M., & Rosenbaum, R.S. (2019). The spacing effect stands up to big data. *Behavior Research Methods*. doi: 10.3758/s13428-018-1184-7

Kim, H. H., & Seo, H. J. (2014). HealthTWITTER initiative: Design of a social networking service based tailored application for diabetes self-management. *Health Informatics Research, 20*(3), 226-230. doi:http://dx.doi.org/10.4258/hir.2014.20.3.226http://dx.doi.org/10.4258/hir.2014.20.3.226

Kirkman, M. S., Briscoe, V. J., Clark, N., Florez, H., Haas, L. B., Halter, J. B., . . . Swift, C. S. (2012). Diabetes in older adults. *Diabetes Care, 35*(12), 2650-2664. doi:10.2337/dc12-1801

Kobayashi, L. C., Wardle, J., Wolf, M. S., & Wagner, C. V. (2014). Aging and functional health literacy. *Journals of Gerontology Series B: Psychogical Sciences and Social Sciences*. doi:10.1093/geronb/gbu161

Krebs, P., Prochaska, J., & Rossi, J. S. (2010). A meta-analysis of computer-tailored interventions for health behavior change. *Preventive Medicine, 51*, 214-221. doi:10.1016/j.ypmed.2010.06.004

Kreuter, M., Bull, F., Clark, E., & Oswald, D. (1999). Understanding how people process health information: A comparison of tailored and nontailored weight-loss materials. *Health psychology, 18*(5), 487-494.

Kreuter, M., & Skinner, C. S. (2000). Tailoring: What's in a name? *Health Education Research, 15*(1), 1-4.

Kreuter, M., & Wray, R. (2003). Tailored and targeted health communication: Strategies for enhancing information relevance. *American Journal of Health Behavior, 27*(Suppl 3), S227-232.

Kuhlthau, C. C. (2010). Guided inquiry: School libraries in the 21st century. *School Libraries Worldwide, 16*(1), 17-28.

Kutner, M., Greenberg, E., Jin, Y., & Paulsen, C. (2006). *The health literacy of America's adults: Results from the 2003 National Assessment of Adult Literacy* Retrieved from Washington, DC: http://nces.ed.gov/pubs2006/2006483.pdf

Levy, H., Janke, A. T., & Langa, K. M. (2014). Health literacy and the digital divide among older americans *Journal of general internal medicine*. doi:10.1007/s11606-014-3069-5

Longo, D. R., Schubert, S. L., Wright, B. A., LeMaster, J., Williams, C. D., & Clore, J. N. (2010). Health information seeking, receipt, and use in diabetes self-management. *Annals of Familiy Medicine, 8*(4), 334-340.

Lustria, M., Cortese, J., Noar, S. M., & Glueckauf, R. (2009). Computer-tailored health interventions delivered over the web: Review an analysis of key components. *Patient education and counseling, 74*(2), 156-173.

Lustria, M., Noar, S. M., Cortese, J., Van Stee, S. K., Glueckauf, R., & Lee, J. (2013). A meta-analysis of web-delivered tailored health behavior change interventions. *Journal of Health Communication, 18*(9), 1039-1069. doi:10.1080/10810730.2013.768727

Lynch, C. P., Williams, J. S., Ruggiero, K., Knapp, R. G., & Egede, L. E. (2016). Tablet-aided behavioral intervention effect on self-management skills (TABLETS) for diabetes. *Trials, 17*(157). doi:10.1186/s13063-016-1243-2

Martinez, J., Ro, M., Villa, N. W., Powell, W., & Knickman, J. R. (2011). Transforming the delivery of care in the post-health reform era: What role will community health workers play? *American journal of public health, 101*(2), e1-e5.

Maslowska, E. (2016). It is all in a name: A study of consumers' responses to personalized communication. *Journal of Interactive Advertising, 16*(1), 74-85. doi:10.1080/15252019.2016.1161568

Mayer, R. E., & Moreno, R. (2003). Nine ways to reduce cognitive load in multimedia learning. *Educational Psychologist, 38*(1), 43-52.

McLannahan, C. & Cornish, C. (2017, September 8). Equifax hackers access details of 143m US consumers. *The Financial Times*.

McGuire, W. J. (1968). *Personality and attitude change: An information-processing theory*. New York, NY: Academic Press, Inc.

Mick, P., Kawachi, I., & Lin, F. R. (2014). The association between hearing loss and social isolation in older adults. *Otolaryngology: Head and Neck Surgery, 150*(3), 378-384.

Misra, S., & Stokols, D. (2011). Psychological and health outcomes of perceived information overload. *Environment and Behavior*.

Mitzner, T. L., McBride, S. E., Barg-Walkow, L., & Rogers, W. A. (2013). Self-management of wellness and illness in an aging population. *Reviews of Human Factors and Ergonomics, 8*(1), 277-333. doi:10.1177/1557234X13492979

Mungas, D., Marshall, S. C., Weldon, N., Haan, M., & Reed, B. (1996). Age and education correction of Mini Mental State Examination for English and Spanish spearking elderly. *Neurology, 46*, 700-706.

National Center for Chronic Disease Prevention and Health Promotion. (2014). National Diabetes Statistics Report, 2014.

National Institute on Deafness and Other Communication Disorders. (2013). *Age-related hearing loss*. Retrieved from http://www.nidcd.nih.gov/health/hearing/Pages/Age-Related-Hearing-Loss.aspx

Neter, E., & Brainin, E. (2012). eHealth literacy: Extending the digital divide to the realm of health information *Journal of Medical Interent Research, 14*(1), e19.

Nguyen, M., Weert, J., Bol, N., Loos, E., Tytgat, K., Ven, A., & Smets, E. (2017). Tailoring the mode of information presentation: Effects on younger and older adults' attention and recall of online information. *Human Communication Research*, 43, 102-126.

Nicholson, N. (2009). Social isolation in older adults: An evolution concept analysis. *Journal of Advanced Nursing, 65*, 1342-1352. doi:10.1111/j.1365-2648.2008.04959.

Nicholson, N. (2012). A review of social isolation: An important but underassessed condition in older adults. *Journal of Primary Prevention, 33*(2-3), 137-152. doi:10.1007/s10935-012-0271-2

Nie, L., Xie, B., Yang, Y., & Shan, Y. M. (2016). Characteristics of Chinese mHealth applications for diabetes selfmanagement. *Telemedicine and eHealth, 22*(7), 1-6.

Nielsen, J. (1993). *Usability inspection methods*. New York: John Wiley & Sons.

Noar, S. M., Benac, C. N., & Harris, M. S. (2007). Does tailoring matter? Meta-analytic review of tailored print health behavior change interventions. *Psychological Bulletin, 133*(4), 673-693. doi:10.1037/0033-2909.133.4.673

Noar, S. M., Harrington, N. G., & Aldrich, R. S. (2009). The role of message tailoring in the development of persuasive health communication messages. *Communication Yearbook, 33*, 73-133.

Noar, S. M., Harrington, N. G., Van Stee, S. K., & Aldrich, R. S. (2011). Tailored health communication to change lifestyle behaviors. *American Journal of Lifesyle Medicine, 5*(2), 112-122. doi:10.1177/1559827610387255

Norman, C., & Skinner, H. A. (2006). eHealth literacy: essential skills for consumer health in a networked world. *Journal of Internet Medical Research, 8*(2).

Norman, G. J., Zabinski, M. F., Adams, M. A., Rosenberg, D. E., Yaroch, A. L., & Atienza, A. A. (2007). A review of eHealth interventions for physical activity and dietary behavior change. *American journal of preventive medicine, 33*(4), 336-345.

Nundy, S., Dick, J. J., Chou, C. H., Nocon, R. S., Chin, M. H., & Peek, M. E. (2014). Mobile phone diabetes project led to improved glycemic control and net savings for Chicago plan participants. *Health Affairs, 33*(2), 265-272.

Oenema, A., Brug, J., & Lechner, L. (2001). Web-based tailored nutrition education: Results of a randomized controlled trial. *Health Education Research, 16*(6), 647-660.

Oldenburg, B., Taylor, C. B., O'Neil, A., Cocker, F., & Cameron, L. D. (2015). Using new technologies to improve the prevention and management of chronic conditions in populations. *Annual review of public health, 36*, 483-505.

Paas, F., & Ayres, P. (2014). Cognitive load theory: A broader view on the role of memory in learning and education. *Educational Psychological Review, 26*(2), 191-195. doi:10.1007/s10648-014-9263-5

Paas, F., & Sweller, J. (2014). Implications of cognitive load theory for multimedia learning In R. E. Mayer (Ed.), *The Cambridge handbook of multimedia learning* (pp. 27-43). New York, NY: Cambridge University Press.

Pachman, M., & Ke, F. (2012). Environmental support hypothesis in designing multimedia training for older adults: Is less always more? *Computers & Education, 58*, 100-110.

Paige, S., Krieger, J., Stellefson, M., & Alber, J. (2017). eHealth literacy chronic disease patients: An item response theory analysis of the eHealth literacy scale (eHEALS). *Patient Education & Counseling*, *100*(2).

Palmas, W., March, D., Darakjy, S., Findley, S. E., Teresi, J., Carrasquillo, O., & Luchsinger, J. A. (2015). Community health worker interventions to improve glycemic control in people with diabetes: A systematic review and meta-analysis. *Journal of general internal medicine*.

Pantell, M., Rehkopf, D., Jutte, D., Syme, L., Balmes, J., & Alder, N. (2013). Social isolation: A predictor of mortality comparable to traditional clinical risk factors. *American journal of public health, 103*(11), 2056-2062.

Park, D. C., & Schwartz, N. (2012). *Cognitive Aging: A primer* New York, NY: Psychology Press.

Pellegrini, C. A., Pfammatter, A. F., Conroy, D. E., & Spring, B. (2015). Smartphone applications to support weight loss: Current perspectives. *Advance Heatlh Care Technology, 1*, 13-22.

Perez-Stable, E. J., Otero-Sabogal, R., Sabogal, F., & Napoles-Springer, A. (1996). Pathways to early cancer detection for Latinas: En Accion Contra el Cancer. *Health Education Quarterly, 23*(Suppl.), S41-S59.

Pillay, J., Armstrong, M., Butalia, S., Donovan, L., Sigal, R., Vandermeer, B., . . . Dryden, D. (2015). Behavioral programs for type 2 diabetes: A systematic review and network meta-analysis. *Annals of Internal Medicine, 163*(11), 848-861.

Powers, M. A., Bardsley, J., Cypress, M., Duker, P., Funnell, M., Fischl, A. H., . . . Vivian, E. (2015). Diabetes self-management education and support in Type 2 diabetes: A joint position statement of the American Diabetes Association, the American Association of Diabetes Educators, and the Academy of Nutrition and Dietetics. *Diabetes Care, 38*, 1372-1382.

Prochaska, J., DiClemente, C. C., & Norcross, J. C. (1992). In search of how people change: Applications to addictive behaviors. *American Psychologist, 47*(9), 1102-1114.

Prochaska, J., DiClemente, C. C., Velicer, W. F., & Rossi, J. S. (1993). Standardized, individualized, interactive and personalized self-help programs for smoking cessation. *Health psychology, 12*(5), 399-405.

Prochaska, J., & Velicer, W. F. (1997). The transtheoretical model of health behavior change. *American Journal of Health Promotion, 12*(1), 38-48. doi:http://dx.doi.org/10.4278/0890-1171-12.1.38

Qi, L., Liu, Q., Qi, X., Wu, N., Tang, W., & Xiong, H. (2015). Effectiveness of peer support for improving glycaemic control in patients with type 2 diabetes: A meta-analysis of randomized controlled trials. *BMC Public Health, 15*, 471-482.

Quinn, C. C., Khokhar, B., Weed, K., Barr, E., & Gruber-Baldini, A. L. (2015). Older adult self-efficacy study of mobile phone diabetes management. *Diabetes Technology & Therapeutics, 17*(7). doi:10.1089/dia.2014.0341

Rabbi, M., Pfammatter, A. F., Zhang, M., Spring, B., & Choudhury, T. (2015). Automated personalized feedback for physical activity and dietary behavior change with mobile phones: A randomized controlled trial on adults. *JMIR Mhealth Uhealth, 14*(3), 10.2196/mhealth.4160.

Radhakrishnan, K. (2011). The efficacy of tailored interventions for self-management outcomes of type 2 diabetes, hypertension or heart disease: a systematic review. *Journal of Advanced Nursing, 68*(3), 496-510.

Rand Corporation (2017). *Multiple chronic conditions in the United States*. Santa Monica, CA: Buttorf, C., Ruder, T., & Bauman, M.

Rainie, L., Kiesler, S., Kang, R., & Madden, M. (2013). Anonymity, privacy, and security online. *Pew Internet & American Life Project*.

Rainie, L., & Smith, A. (2013). Tablet and e-reader ownership update. *Pew Internet & American Life Project*.

Rains, S. (2012). The nature of psychological reactance revisited: A meta-analytic review. *Health Communication Research, 39*(1), 47-73.

Reijnders et al., (2015) Cognitive interventions in healthy older adults and people with mild cognitive impairment: A systematic review. *Aging & Decision Making*, 149-168.

Ricci-Cabello, I., Ruiz-Perez, I., Rojas-Garcia, A., Pastor, G., Rodriguez-Barranco, M., & Goncalves, D. (2014). Characteristics and effectiveness of diabetes self-management educational programs targeted to racial/ethnic minorities: A systematic review, meta-analysis and meta-regression. *BMC Endocrine Disorders*(14). doi:10.1186/1472-6823-14-60.

Rimer, B. K., & Kreuter, M. (2006). Advancing tailored health communication: A persuasion and effects perspective. *Journal of Communication, 56*, S184-S201.

Rogers, E. A., Hessler, D. M., Ghorob, A., Vittinghoff, E., & Thorn, D. H. (2014). Diabetes peer coaching: Do 'better patients' make better coaches? *The Diabetes Educator, 40*(1), 107-115.

Rothschild, S. K., Martin, M. A., Swider, S. M., Lynas, C. T., Avery, E. F., Janssen, I., & Powell, L. H. (2012). The Mexican-American Trial of Community Health workers (MATCH): Design and baseline characteristics of a randomized controlled trial testing a culturally tailored community diabetes self-management intervention. *Contemporary clinical trials, 33*, 369-377.

Rothschild, S. K., Martin, M. A., Swinder, S. M., Tumialan, C. M., Janssen, I., Avery, E. F., & Powell, L. H. (2014). Mexican American trial of community health workers: A randomized controlled trial of a community health worker intervention for Mexian Americans with type 2 diabetes. *American journal of public health, 104*(8), 1540-1548. doi:10.2105/AJPH.2013.301439

Rush, C. (2012). Return on investment from employment of community health workers. *Journal of Ambulatory Care Management, 35*(2).

Sadasivam, R. S., Cutrona, S. L., Kinney, R. L., Marlin, B. M., Mazor, K. M., Lemon, S. C., & Houston, T. K. (2016). Collective-intelligence recommender systems: Advancing computer tailoring for health behavior change into the 21st century. *Journal of Medical Interent Research, 18*(3), e42. doi:10.2196/jmir.4448

Salthouse, T. (2010). *Major Issues in Cognitive Aging*. New York, NY: Oxford University Press.

Schick, A. G., & Gordon, L. A. (1990). Information overload: A temporal approach. *Accounting, Organizations, and Society, 15*(3), 199-220.

Schiotz, M. L., Bogelund, M., Almdal, T., Jenson, B. B., & Williang, I. (2012). Social support and self-management behaviour among patients with Type 2 diabetes. *Diabetes Medicine, 29*, 654-661.

Schmidt, K., Collinsworth, A., Barnes, S., Brown, R., Kane, E., Snead, C., & Fleming, N. S. (2015). Impact of a community health worker-led diabetes education program on hospital and emergency department utilization and costs. *Journal of Clinical Outcomes Management, 22*(5), 204-210.

Serrano, K., Yu, M., Riley, W.T., Patel, V., Hughes, P., Marchesini, K., & Atienza, A.A. (2016). Willingness to exchange health information via mobile devices: Findings from a population-based survey. *Annals of Family Medicine*, *14*(1), 34-40.

Shankar, A., McMunn, A., Banks, J., & Steptoe, A. (2011). Loneliness, social isolation, and behavioral and biological health indicators in older adults. *Health psychology, 30*(4), 377-385.

Shen, L. (2015). Antecedents to psychological reactance: The impact of threat, message frame, and choice. *Health Communication, 30*(10), 975-985.

Sherifali, D., Bai, J. W., Kenny, M., Warren, R., & Ali, M. U. (2015). Diabetes self-management programmes in older adults: A systematic review and meta-analysis. *Diabetic Medicine, 32*(11), 1404-1414. doi:10.1111/dme.12780

Skinner, C. S., Campbell, M. K., Rimer, B. K., Curry, S., & Prochaska, J. (1999). How effective is tailored print communications? *Annals of Behavioral Medicine, 21*(4), 290-298. doi:10.1007/BF02895960

Skinner, C. S., Strecher, V. J., & Hospers, H. (1994). Physicians' recommendations for mammography: Do tailored messages make a difference? *American journal of public health, 84*(1), 43-49.

Smith, W. R. (1956). Product differentiation and market segmentation as alternatie marketing strategies. *Journal of Marketing*.

Smith, A., Anderson, M., & Page, D. (2017). Tech adoption climbs among older adults. *Pew Research Center*. Retreived from: http://www.pewinternet.org/2017/05/17/technology-use-among-seniors/

Steinsbekk, A., Rygg, L., Lisulo, M., Rise, M. B., & Fretheim, A. (2012). Group based diabetes self-management education compared to routine treatment for people with type diabetes mellitus. A systematic review with meta-analysis. *BMC Health Services Research, 12*(213).

Strom, J. L., & Egede, L. E. (2012). The impact of social support on outcomes in adult patients with Type 2 diabetes: A systematic review. *Current Diabetes Reports, 12*(6), 769-781.

Sugiyama, T., Steers, W. N., Wenger, N. S., Duru, O. K., & Mangione, C. M. (2015). Effect of a community-based diabetes self-management empowerment program on mental health-related quality of life: A causal mediation analysis from a randomized controlled trial. *15, 155*.

Sun, A. C., Tsoh, J. Y., Saw, A., Chan, J. L., & Cheng, J. W. (2012). Effectiveness *Diabetes Educator, 38*(5), 685-694.

Taylor, K. L., Weston, M., & Batterham, A. M. (2015). Evaluating intervention fidelity: An example from a high-intensity interval training study. *PLoS One, 10*(4), 1-8. doi:doi:10.1371/journal.pone.0125166

Tougas, M. E., Hayden, J. A., McGrath, P. J., Huguet, A., & Rozario, S. (2015). A systematic review exploring the social cognitive theory to self-regulation as a framework for chronic health conditions *PLoS One, 10*(8), e0134977.

Tovar, E., Rayens, M. K., Gokun, Y., & Clark, M. (2013). Mediators of adherence among adult with comorbid diabetes and depression: The role of self-efficacy and social support *Journal of Health Psychology*. doi:10.1177/1359105313512514

Trewartha, K. M., Garcia, A., Wolpert, D. M., & Flanagan, J. R. (2014). Fast but fleeting: Adaptive motor learning processes associated with aging and cognitive decline. *The Journal of Neuroscience, 34*(40), 13411-13421. doi:10.1523/JNEUROSCI.1489-14.2014

United States Census Bureau. (2015). *QuickFacts*. Retrieved from https://www.census.gov/quickfacts/table/PST045215/0600562/accessible

Updegraff, J. A., Brick, C., Emanuel, A. S., Mintzer, R. E., & Sherman, D. K. (2015). Message framing for health: Moderation by perceived susceptibility and motivational orientation in a diverse sample of americans. *Health psychology, 34*(1), 20-29. doi:10.1037/hea0000101

Van Gerven, P., Paas, F., & Tabbers, H. (2006). Cognitive aging and computer-based instructional design: Where do we go from here? *Educational Psychology Review, 18*(2), 141-157.

Velicer, W. F., Prochaska, J., Fava, J. L., Laforge, R. G., & Rossi, J. S. (1999). Interactive versus noninteractive interventions and dose-response relationships for stage-matched smoking cessation programs in managered care settings. *Health psychology, 18*, 21-28.

Verheijden, M. W., Jans, M. P., Hildebrandt, V. H., & Hopman-Rock, M. (2007). Rates and determinants of repeated participation in a web-based behavior change program for healthy body weight and healthy lifestyle. *Journal of Medical Interent Research, 9*(1), e1. doi:10.2196/jmir.9.1.e1

Vincent, D., & Pasvogel, A. (2007). A feasibility study of a culturally tailored diabetes intervention for Mexican Americans. *Biological Research Nursing, 9*(2), 130-141. doi:10.1177/1099800407304980

Weymann, N., Harter, M., & Dirmaier, J. (2013). A tailored, interactive health communication application for patients with type 2 diabetes: Study protocol of a randomised controlled trial. *BMC Medical Informatics & Decision Making, 13*(24).

Whitley, E. M., Everhart, R. M., & Wright, R. A. (2006). Measuring return on investment of outreach by community health workers. *Journal of Health Care for the Poor and Underserved, 17*(1), 6-15.

Wilson, T. D. (2001). Information overload: Implications for healthcare services. *Health Informatics Journal, 7*, 112-117.

Wong, R. H., Scholey, A., & Howe, P. R. (2014). Assessing premorbid cognitive ability in adults with Type 2 diabetes mellitus - A review with implication for future intervention studies *Current Diabetes Reports, 14*.

Xie, B. (2011). Experimenting on the impact of learning methods and information presentation channels on older adults' e-health literacy. *Journal of the American Society for Information Science and Technology (JASIST), 62*(9), 1797-1807. doi:10.1002/asi.21575

Xie, B., Wang, M., Feldman, R., & Zhou, L. (2010). *Health information and decision-making preferences in the Internet age: A pilot study using the Health Information Wants Questionnaire* Paper presented at the ACM International Health Informatics Symposium, Arlington, VA.

Xie, B., Wang, M., Feldman, R., & Zhou, L. (2013). Internet use frequency and patient-centered care: Measuring patient preferences for participation using the health information wants questionnaire. *Journal of Medical Interent Research, 15*(7), e132.

York, C. (2013). Overloaded by news: Effects of news exposure and enjoyment on reporting information overload. *Communication Research Reports, 30*(4), 282-292.

Yu, C. H., Parsons, J. A., Hall, S., Newton, D., Jovicic, A., Lottridge, D., . . . Straus, S. E. (2014). User-centered design of a web-based self-management site for individuals with type 2 diabetes: Providing a sense of control and community. *BMC Medical Informatics and Decision Making, 14*. doi:10.1186/1472-6947-14-60

Zaval, L., Li, Y., Johnson, E.J. & Weber, E. (2015). Complementary contributions of fluid and crystallized intelligence to decision making across the life span. *Aging and Decision Making*, 148-168.

Zins, C. (2007). Conceptual approaches for defining data, information, and knowledge. *Journal of the Association for Information and Science and Technology (JASIST), 58*(4), 479-493. doi:10.1002/asi.20508