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Evaluating the Persuasiveness of Mobile Health: The Intersection of Persuasive System Design and Data Science

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EVALUATING THE PERSUASIVENESS OF MOBILE HEALTH: THE INTERSECTION OF PERSUASIVE SYSTEM DESIGN AND DATA SCIENCE

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I dedicate this dissertation to the memory of my father, Rev. LeRoy Henry, III, whose role in my life was, and remains, immense. Your words confirmed those that were spoken to me by Dean Eric Jack, and with them my journey began. While you aren’t here for the end of my journey, your words of encouragement still ring in my ears. You are truly the wind beneath my wings.

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TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABREVIATIONS

Abbreviation	Meaning
AH	Adult Hope
Big 5	Big 5 Personality Trait
CFA	Confirmatory Factor Analysis
CSM	Contrast Set Mining
DS	Dialogue Support
EFA	Exploratory Factor Analysis
EPM	Emerging Pattern Mining
HC	Health Consciousness
mHealth	Mobile Health
MLR	Multiple Linear Regression
MV	Marker Variable
PP	Perceived Persuasiveness
PSD	Persuasive Systems Design
PT	Primary Task Support
SC	System Credibility
SE	Self-Efficacy

Abbreviation	Meaning
SS	Social Support
STUCCO	Search and Testing for Understandable Consistent Contrasts

ABSTRACT

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Persuasive technology is an umbrella term that encompasses any software (e.g., mobile app) or hardware (e.g., smartwatch) designed to influence users to perform a preferable behavior once or on a long-term basis. Considering the ubiquitous nature of mobile devices across all socioeconomic groups, user behavior modification thrives under the personalized care that persuasive technology can offer. This research examines the roles psychological characteristics play in interpreted mHealth screen perceived persuasiveness. A review of the literature revealed a gap regarding how developers of digital health technologies are often tasked with developing tools designed to engage patients, yet little emphasis has been placed on understanding what psychological characteristics motivate and demotivate their users to engage with digital health technologies. Developers must move past using a cookie-cutter, one size fits all solution, and seek to develop digital health technologies designed to traverse the terrain that navigates between the fluid nature of goals and user preferences. This terrain is often determined by user's psychological characteristics and demographic (control) variables. An experiment was designed to evaluate how psychological characteristics (self-efficacy, health consciousness, health motivation, and the Big Five personality traits) impact the perceived persuasiveness of digital health technologies utilizing the Persuasive System Design (PSD) framework. This study used multiple linear regressions and Contrast, a publicly available Python implementation of the contrast pattern mining algorithm Search and Testing for Understandable Consistent Contrasts (STUCCO), to study the multifaceted needs of the users of digital health technologies based on psychological characteristics. The results of this experiment show psychological characteristics (self-efficacy, health consciousness, health motivation, and extraversion) enhancing the perceived persuasiveness of digital health technologies. The findings of the study revealed that screens utilizing techniques for the primary task support have high perceived persuasiveness scores. System credibility techniques were found to be a contributor to perceived persuasiveness and should be used in the development of persuasive technologies. The results of this study show practitioners should abstain from using social support techniques. Persuasive techniques from the social support category were found to have very low perceived persuasive scores which indicate a lower ability to persuade mHealth app users to utilize the tool. The findings strongly suggest the distribution of perceived persuasiveness shifts from negatively skewed to positively skewed as participants get older. Additionally, this shift occurs earlier in females (i.e., in the 40-59 age group) compared to males who do not shift until the oldest age group (i.e., in the 60 and older age group). The results imply that an individual user’s psychological characteristics affect interpreted mHealth screen perceived persuasiveness, and that combinations of persuasive principles and psychological characteristics lead to greater perceived persuasiveness.

CHAPTER I

INTRODUCTION

Given the ubiquitous nature of mobile devices across all socioeconomic groups, digital health technologies have demonstrated their efficacy as a key component in educating and treating patients (Matthews et al., 2016). Mobile health (mHealth) uses mobile devices to practice medicine and public health. Unlike clinic-based treatments where data is sparingly gathered, the ever-present nature of digital health technologies allows for an extensive more intimate treatment plan. While digital health technologies allow for the real-time transfer of user data, which allows for more intimate user interaction, these technologies are met with a unique set of challenges, such as creating and maintaining engagement (Birnbaum et al., 2015). The efficacy of digital health technologies relies strongly on the ability to continuously engage and reengage the user (O'Brien, 2018). The closed-loop engagement process begins with engagement and continuously moves through disengagement only to have the patient reengage upon disengagement (O'Brien & Toms, 2008; Taki et al., 2017). Properly engaging patients has repeatedly been shown to improve patient outcomes (Birnbaum et al., 2015).

However, at the core of engagement using digital health technologies, there remains a gap in the literature as to how to successfully design these tools based on the individual consumers dynamic psychological makeup. For instance, there remains a need to learn more about how mHealth treatments work and how to make them more effective, in particular research on the impact of certain intervention features on user engagement is an important next step in the development of theory and evaluation to develop a science for user engagement (Vandelanotte et al., 2016). While the positive influence that persuasion has on changing an individual's attitude and behavior has been established (MScMed & BOccTher, 2019; Orji & Moffatt, 2018), researchers have contended the need for personalized systems that address the individual's personality to increase the effectiveness of these tools (Kaptein et al., 2015; Wall et al., 2019). One-size-fits-all digital health technologies that target behavioral change to improve the user's health often fail because they do not target the psychological traits that drive an individual's motivations and behaviors, due in part to the lack of guidance intervention designers and data scientists with numerous options face (Engl et al., 2019). A dynamic personalized approach to the development of persuasive technologies is imperative as research has shown that strategies that may influence change in an individual with one type of psychological type may dissuade another individual with a different psychological type (Abdullahi, Oyibo, et al., 2019).

User engagement is a widely used multifaceted term that extends beyond a user's desire to use of digital health technologies to the depth of the user's investment (O'Brien et al., 2020). Developers of digital health technologies are often tasked with developing tools designed to engage patients, yet little emphasis has been placed on understanding what motivates their users to engage with digital health technologies. Developers must move past using a cookie-cutter, one size fits all solution, and seek to develop digital health technologies designed to traverse the fluid terrain that navigates between the expectations of the user and the technological capabilities of the tool. The fluid nature of goals and user preferences determined by user characteristics must also be considered to foster various engagement trajectories with digital health technologies. Synonymous with the engagement process, the development of digital health technologies must be dynamic in nature, traversing between design and redesign guided by use (Goldkuhl, 2013). The unconscious disregard of the interdependency between technology, human characteristics, and the socio-economic environment has been determined to be one of the factors in digital health technologies failing to sustain innovations in the healthcare field (Michie et al., 2017; Van Gemert-Pijnen et al., 2011).

Persuasive technology has emerged as a significant contributor to patient engagement and is being used practically in every area of health and wellness (Karekla et al., 2019; Orji & Moffatt, 2018). Persuasive Technology is an umbrella term that encompasses any software (e.g., mobile app) or hardware (e.g., smartwatch) designed with the intent to influence users to either perform a preferable behavior once or on a long-term basis. These modifications must be achieved without the use of deception, coercion, or inducements (Iyengar et al., 2009b; R. Orji et al., 2018). By adequately applying persuasive technology, intervention developers have the potential to improve patient outcomes by closing the engagement loop successfully. The modification of user behavior thrives under the personalized care that persuasive technology has to offer. However, absent from the current literature is adequate information on "how" app designers are to operationalize persuasive design principles based on a more user centric view (Thomson et al., 2016). Research is immersed in studies related to the user experience derived from metrics and quantifications, but there remains a void in the literature seeking a more intimate view of the consumer and how they interact with persuasive principles in order to help guide the design processes. The design process is furthered impaired by the lack of an understanding of the psychological characteristics of digital health technology users (Tuman & Moyer, 2019). Past research has focused on the development of theories concentrated on predicting acceptance or adherence instead of guiding persuasive technology design principles (Al-Ramahi et al., 2016).

This research is needed to fill the gap in the literature addressing user centric development of persuasive technologies and developing a better understanding of psychological characteristics necessary for the successful engagement of digital health technology users. To answer these questions, insight is needed into what roles psychological characteristics play in interpreted mHealth screen perceived persuasiveness. Broadening the PSD framework, based on the user's psychological characteristics will address the dynamic needs of the users of digital health technologies. This research is guided by two research questions specifically: (1) How do individual user's psychological characteristics effect interpreted mHealth screen perceived persuasiveness? (2) What specific combinations of persuasive principles utilizing mHealth screens and psychological characteristics will lead to greater perceived persuasiveness?

This paper is organized into six chapters, included the present chapter. Chapter II reviews the existing literature on narrative engagement and persuasive technology in a dynamic context and discusses the limitation of the current research. Chapter III develops the formal hypotheses regarding expected effects of psychological characteristics on interpreted mHealth screen perceived persuasiveness and develops the data science technique used to investigate significant differences between groups of users. Chapter IV details the proposed statistical methods to quantitatively investigate the hypotheses and the proposed data science approach to extract significant differences between groups of users. Chapter V discusses the modified methodology and the results of the analysis. Chapter VI includes a discussion regarding the findings and outlines the limitations and future works related to this research.

CHAPTER II

LITERATURE REVIEW

The following section begins by presenting what are the driving influences in consumer engagement and defines the critical terms that are important to advancing perceived persuasiveness in digital health technologies. Also included is an extensive literary review, presenting an overarching view of why persuasive digital health technologies should be dynamic in nature as opposed to one-size-fits-all solutions.

2.1 Engagement

The term engagement has been used multiple ways, often depending on the discipline seeking to conceptualize it. The ability to engage system users is a highly sought-after goal when designing systems. The vast models and measures being proposed through multidisciplinary research are arduous to unify (Barello et al., 2014). Researchers draw on multiple disciplines, such as psychology, marketing, gamification, and human-computer interaction (Yardley, Spring, et al., 2016). This complex and multifaceted term is even more complex to quantify, as it is often influenced by factors such as culture, family, and internal motivators (Taki et al., 2017). The focus of engagement definitions varies by discipline and range from the perspective of the intervention user to the ability of the system designer to draw the user in and motivate interaction (Lalmas et al., 2014;

Walker et al., 2017). The lack of an explicit foundation presents challenges when trying to obtain consistent objectives and goals.

Engaging users of digital health technologies should result in societal and individual improvement in modifying individual's health behaviors. The use of digital health technologies should improve both consumer/patient engagement and experience (Tai-Seale et al., 2019). Engagement is not dependent upon the entertainment of a tool but instead on whether the user is extensively engrossed and aligned with the tool (Higgins et al., 2017). While indicators of user activity are often used to measure engagement, these behaviors do not consider the multiple dimensions of the user's digital interactions and fail to paint a complete picture (O'Brien, 2018). Intervention usage is a valid indicator of engagement, but additional measurements including quantitative measures (i.e., using system usage data to encapsulate how the digital health technology is physically used by the participant) should be used to assess the engagement of digital health technologies (Short et al., 2018).

One of the most critical factors in the success of digital behavior change tools is the successful engagement of users. When analyzing consumer/patient engagement with digital behavior change tools a distinction between micro immediate and continuous engagement and broad macro levels of engagement must be made (Yardley, Spring, et al., 2016). Despite the exponential growth in the development of digital health technologies, few studies have quantified user engagement with these digital behavior change tools (Holdener et al., 2020). Cost, time, and data analysis constraints often hinder extensive research in the use and validity of digital behavior change tools. Researchers often alleviate this by utilizing expertise from other appliable (sub)disciplines such as human-computer interaction and health informatics (Short et al., 2018). However, different disciplines (e.g., health informatics, computer science) define engagement differently, making it difficult to form a synthesized consensus of what engages users, further hindering the development of recommendations for the developers of digital behavior change tools (Karekla et al., 2019). As interdisciplinary models of engagement emerge, determining the essential components to actively engage users has been identified as a key research priority (Yardley, Spring, et al., 2016).

2.2 Consumer Health Engagement

Consumer engagement is the utilization of strategies designed to promote engagement and foster a desire for the user to interact with the digital health technology (Alkhaldi et al., 2016). Synonymous with the recent augmentation of digital health technologies is the alacrity in which users abandon these interventions following minimal use (Holdener et al., 2020). One of the most critical tasks is the successful engagement of digital health technology users and consumer engagement has been cited as one of the key determinants in the successfulness of a digital health technology (Birnbaum et al., 2015; Holdener et al., 2020). Consumer engagement is multidimensional and viewed in a myriad of ways.

In its infancy, consumer engagement was often defined as a response to digital health technologies that maintain and stimulate the user's attention (Kim et al., 2013). Using this standard, the point of engagement is established when the digital health technology aesthetically or informationally arouses the user and can be defined using measures of attention focus, curiosity, and intrinsic interest (Chapman et al., 1999;

O'Brien & Toms, 2008). There exists a paradigm shift in the literature where researchers extended the qualifications for engagement. Researchers began to hone in on the principle of user engagement being driven by the quality of the users/patients experience (Holdener et al., 2020; Lalmas et al., 2014; Taki et al., 2017). While others also measured engagement by the interaction with digital health technologies, often driven by attributes that naturally evoke interest in the consumer, often believed to be reflected by behavior change in the user (Ren et al., 2019; Zagalo, 2020). Engagement is also seen as a synergized relationship between digital health technology and the consumer, in which the consumer is fully immersed and aligned with the activity (Salehzadeh Niksirat et al., 2018).

User engagement is also driven by user characteristics. For example, emotional and behavioral characteristics are considered driving factors for the time and energy users are willing to expend (O'Brien et al., 2020). Breaking from previous more experience-oriented perspectives of engagement, current engagement concepts require the users to give their undivided attention to the digital health technology (Ren et al., 2019). Achieving synergy between digital health technologies and consumers is often considered the highest form of user engagement (Salehzadeh Niksirat et al., 2018). As smartphones and other conduits for the delivery of digital health technologies become more ubiquitous, designers are capable of incorporating customization features to engage users/patients (Lalmas et al., 2014).

2.3 Effective Engagement

There is a general consensus that an implicit level of engagement is required for digital health technologies to be effective. The absence of engagement impedes digital health technologies from reaching their full potential (Alkhaldi et al., 2016). This emerging stream of research is built on a somewhat challenging and unstable foundation as authors use various procedures to measure engagement (Holdener et al., 2020). With various metrics in play, the ability to quantify engagement is a very daunting and challenging task (Holdener et al., 2020; Zagalo, 2020). This obstruction further exasperates our efforts to assess effective engagement.

Digital health technology developers must exercise quantitative and qualitative methods when seeking to design engaging applications (Sahin, 2018). Quantitative measures evaluating the intensity and breadth of use are often used to determine the level of consumer engagement (Helsper & Eynon, 2013). Such a holistic view is not always feasible for developers, but the use of tangible metrics (e.g. the amount of screen time of the digital health technology, the number of likes and shares) can be quantified and used for quantitative data (O'Brien, 2018). For engagement to be meaningful, digital health technologies must modify user behavior and advance ordinary experiences into aesthetically pleasing experiences (Salehzadeh Niksirat et al., 2018). Qualitative measures evaluating engagement include interviews, observations, and the utilization of focus groups to assess the digital health technology user's experience with the intervention (Short et al., 2018). These methods allow for a structured, regulated, and convenient measurement of engagement.

Chapman et al. (1999) proposed that engagement was dichotomous, being either less passive or more passive based on the level of control. More controlled engagement requires information processing such as critical thinking and reasoning and involves a less passive state of engagement. Passive engagement requires less control and is easier to achieve because the level of effort and motivation are low. While easier to achieve and maintain, passive engagement is less useful in the successful achievement of established goals that require high levels of cognition (Chapman et al., 1999).

The delivery of properly tailored digital health technology content can increase users' engagement and positively influence outcomes. This makes the understanding of how to design digital health technologies based on patient/consumer preferences all the more imperative (Tarute et al., 2017). Identifying the features of digital health technologies that stimulate engagement in users is crucial in the development of effective tools (Tuman & Moyer, 2019). One of the key factors to developing digital health technologies that enhance engagement through the aforementioned techniques is persuasive technology.

2.4 Persuasive Technology

Persuasive Technology is an umbrella term that encompasses any software (e.g., mobile app) or hardware (e.g., smartwatch) designed with the intent to persuade users to either perform a preferable behavior once or on a long-term basis (Guimaraes et al., 2018). These modifications must be achieved without the use of deception, coercion, or inducements (Iyengar et al., 2009a; R. Orji et al., 2019). B.J. Fogg (2009a, 2009b) defines persuasive technologies as a ubiquitous group of technologies or interactive computing systems designed to modify a user's attitude or behavior. Persuasive technologies depend on engagement in order to successfully achieve these goals (Russell, 2011).

Fogg (2003a) posits that persuasive technologies can play one of the following roles from what he termed the functional triad: tools (make user's actions easier or more efficient), media (deliver interactive and engaging content to users), and social (able to simulate a living body) (Irizar-Arrieta et al., 2020). Persuasive technologies have been utilized across multiple domains, however, the health-related domain has employed persuasive technologies more prevalently (Abdullahi, Oyibo, et al., 2019; Sara & Mostafa, 2019; Spelt et al., 2019; Trujillo et al., 2018). Persuasive technologies provide a conduit for digital health technology designers to target specific behaviors in users in order to promote healthier lifestyles and treat and/or prevent disease through increased digital health engagement. The impact of persuasive digital health technologies are far reaching, offering opportunities to improve disease prevention and management through increased engagement (Matthews et al., 2016).

According to Fogg (2009a), the threefold focus of persuasive systems design centers on increasing stakeholder motivation, abilities, and triggering stakeholder behavior (Fogg, 2009c). Many designers and developers of persuasive technologies attempt to create these digital health technologies without using formal persuasive design approaches as the underlying foundation (Taype & Calani, 2020). Fogg's design framework presents five persuasive design principles (reduction, tunneling, tailoring, self-monitoring, and suggestion) and seeks to explain the cause of stakeholder behavior (Fogg, 2003b). Oinas-Kukkonen and Harjumaa (2009) proposed a model that extends

Fogg's five original principles to include twenty-three additional principles (personalization, simulation, rehearsal, praise, rewards, reminders, similarity, liking, social role, trustworthiness, expertise, surface credibility, real world feel, authority, third party endorsements, verifiability, social learning, social comparison, normative influence, social facilitation, cooperation, competition, and recognition) and provides methods for evaluating persuasive system development.

More recent persuasive design frameworks have been inspired by the principles presented by Fogg (2009a, 2009c) and Oinas-Kukkonen and Harjumaa (2009). Stibe (2015) leverages the seven principles from Oinas-Kukkonen's (2009) social support category (social learning, social comparison, normative influence, social facilitation, cooperation, competition, and recognition) to modify the behavior and attitude of stakeholders. Murillo-Munoz et al. (2018) proposed a framework for the design of persuasive systems which utilizes the twenty-eight principles proposed by Oinas-Kukkonen (2009).

2.4.1 Persuasive Systems Design Principles

Excluding Fogg's Persuasive Technology framework, Oinas-Kukkonen (2008, 2009) Persuasive Systems Design (PSD) framework (Figure 1) is one of the most cited persuasive technology models. Finding Fogg's framework to be too general, Oinas-Kukkonen aimed to discuss with more depth the persuasive technology design and evaluation process. Based strongly on Fogg's functional triad, the PSD is a systematic, detail-oriented framework that outlines the premise, persuasion context, and the

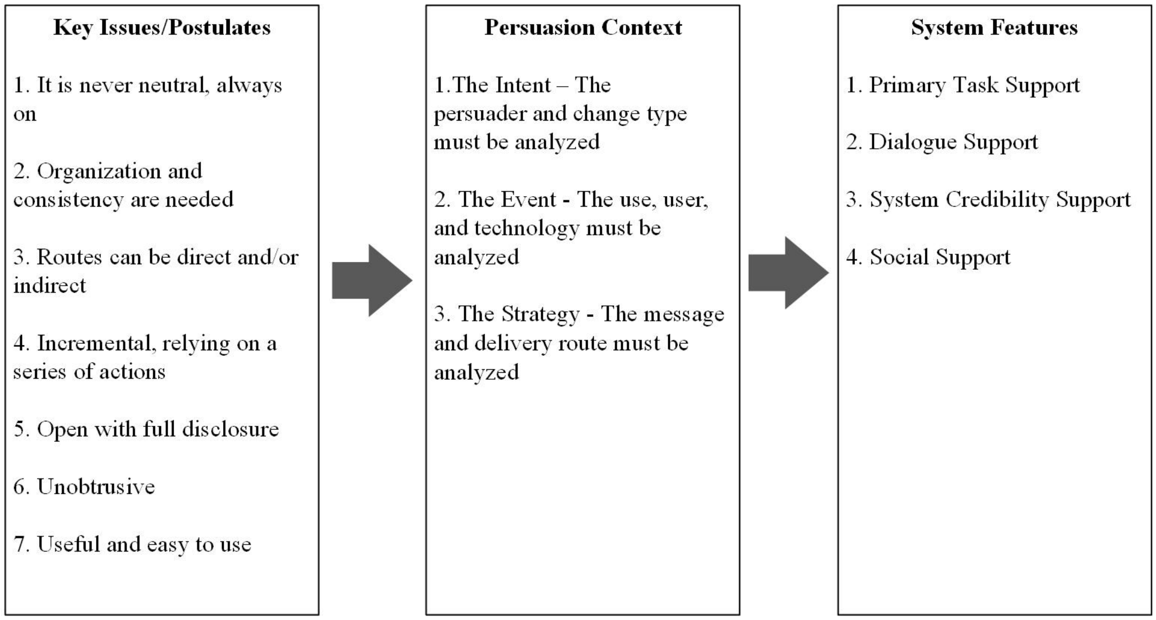

Figure 1. Persuasive System Design Model (Oinas-Kukkonen & Harjumaa, 2009)

contextual factors designers must analyze in persuasive systems (Valter et al., 2018). The seven postulates that must be addressed and considered during the persuasive systems design process include (Oinas-Kukkonen & Harjumaa, 2008, 2009):

1. Technology is never neutral; it constantly influences the user's behavior and attitudes.
2. Users prefer for their views about the world be organized and consistent.
3. Routes to persuasion can be direct and indirect. These routes are not mutually exclusive, instead they may be used simultaneously depending on the user's personal background, motivation, and ability.
4. Persuasion is often incremental, relying on a series of actions which lead to a specific goal.

5. Persuasive technologies should be open, designers must utilize truthful content and disclose all bias and goals.
6. Persuasive technologies must be unobtrusive, taking precautions to only engage users during opportune moments.
7. Persuasive technologies should be useful and easy to use.

Analyzing the persuasion context requires examining (Oinas-Kukkonen & Harjumaa, 2009):

1. The intent - When analyzing intent, developers must consider if the persuasion aims to change the attitude, behavior, or both.
2. The event - The use and user context must be considered.
3. The strategy – The message and delivery route must be analyzed when defining persuasive strategies.

PSD provides twenty-eight persuasive design techniques categorized as primary task support, dialogue support, system credibility support, or social support based on persuasive features (Oinas-Kukkonen & Harjumaa, 2008, 2009).

1. The Primary Task Support (PT) category aids the user in performing their fundamental tasks. Primary task principles include reduction, tunneling, tailoring, personalization, self-monitoring, simulation, and rehearsal.
2. Dialogue Support (DS) facilitates dialogue between the persuasive system and the user. The principles that are used to provide feedback are praise, rewards, reminders, suggestion, similarity, liking, and social role.
3. The System Credibility (SC) category delineates how to make systems more credible thereby making them more persuasive. The principles that are used to

give credibility include trustworthiness, expertise, surface credibility, real-world feel, authority, third-party endorsements, and verifiability.

4. The Social Support (SS) category leverages social influence in order to motivate system users. The design principles in this category include social facilitation, social comparison, normative influence, social learning, cooperation, competition, and recognition.

Absent from the PSD is guidance outlining a standardized process for persuasive system designers on how to analyze and utilize the most appropriate technologies to make the system persuasive (Kelders et al., 2016; Matthews et al., 2016; Oinas-Kukkonen, 2012; Orji & Moffatt, 2018). The importance of dynamic content is most visible in the indirect and direct route postulate. It is also highly visible in the evaluation of the event persuasion context. Event analyzation has cognitive determinants varying based on factors such as the user's interests, goals, motivations, and pre-existing (Oinas-Kukkonen & Harjumaa, 2009).

2.5 Perceived Persuasiveness

Perceived persuasiveness is defined as the degree to which an individual views the strength of a persuasion embedded in the system being evaluated (Zhang et al., 2014). Perceived persuasiveness and behavior modification have been studied across multiple domains. A system with a high degree of perceived persuasiveness promotes a positive impression from the individual user (Drozd et al., 2012). More recently, perceived persuasiveness has been regarded as the capability of a system to persuade an individual to accept it in order to motivate the targeted behavior change through the system's user-experience design (Oyibo & Vassileva, 2020). Leaving authors to postulate that perceived persuasiveness should be viewed as an end result of persuasion (Beerlage-de Jong et al., 2020). Pangbourne (2020) studied the effects of personality on the perceived persuasiveness of tailored messages designed to encourage walking during travel planning. This study which made use of the Big 5 found that the age and personality of individuals have an impact on perceived persuasiveness.

The Persuasive Systems Design model was designed to serve as a guideline for developers seeking to build persuasive systems (Oinas-Kukkonen & Harjumaa, 2009). Previous research shows that the Persuasive Systems Design categories in the PSD model have a significant impact on perceived persuasiveness. Drozd et al. (2012) conducted a study that determined Primary Task Support and Dialogue Support together significantly impacted perceived persuasiveness. They found that the direct relationship between Primary Task Support and perceived persuasiveness was not significant. However, Lehto et al. (2012) found Primary Task Support, System Credibility, and Dialogue Support to all significantly impact perceived persuasiveness directly. As with the previous study, Dialogue Support and Primary Task Support was found to have a significant connection to perceived persuasiveness. Additionally, System Credibility and Dialogue Support were also found to have a significant connection to perceived persuasiveness.

2.6 No One-Size-Fits-All Solution

Characteristics such as gender, age, and personalities affect how users respond to persuasive technologies, causing a pivot from one-size-fits-all solutions to a more user-centric approach (Abdullahi, Oyibo, et al., 2019). Persuasive technologies are able to adapt to individualized characteristics of users, increasing their likelihood of changing the users behavior or attitude (Wiafe, 2018). Studies show that persuasive technologies that personalize content instead of utilizing one size fits all approaches are more successful at effectively persuading users (Gena et al., 2019; Orji et al., 2015; Orji et al., 2014). One-size-fits-all persuasive technologies can be enhanced when the user's individual attitudes and characteristics are used to influence and personalized the persuasiveness of the intervention (Berkovsky et al., 2012).

While research has shown individualized persuasive technology to be more effective than persuasive technology designed from a one-size-fits-all perspective (F. A. Orji et al., 2019; Orji et al., 2013; Ruijten, 2020), developers often fail to consider the individualized behavior of stakeholders and how it impacts achieving a target behavior (Taype & Calani, 2020). Digital health technologies that deviate from compartmentalized one-size-fits-all approaches offer a medium through which health care providers can meet the growing demands of users preferring a more personalized approach (Almunawar et al., 2015; Sahin, 2018). This growing demand necessitates the ability to understand how to design digital health technologies dynamic enough to accommodate the differing predispositions of end-users (Tarute et al., 2017).

Designers must understand how to tailor digital health technologies to individual characteristics to effectively engage users with these tools. By tailoring digital health technologies to users' characteristics, developers are able to deliver guidance that is appropriate, relevant, and has a positive impact on engagement (Yardley, Choudhury, et al., 2016). The disregard for the interconnectedness between human characteristics and technology is one reason digital health technologies inevitably become high tech with little to no impact (Keizer et al., 2020). Current theories are inept to inform digital health technology developers as to how to develop and evaluate more adaptive interventions (Nahum-Shani et al., 2018; Riley et al., 2011). Recognizing the psychological characteristics of end-users will better allow developers to systematically approach the integration of persuasive design components into digital health technologies.

Data-centered persuasive technologies seek to modify user attitudes or behaviors by utilizing user's behavioral data (Shin & Kim, 2018). Today's technology allows intervention designers to dynamically generate personalized interventions based on the specific user's personal characteristics (Dalecke & Karlsen, 2020). Dynamic approaches acknowledge that interventions designed for one user may not necessarily fit the model needed to effectively engage another user. A user's characteristics often dictate the most effective persuasive technique (Berkovsky et al., 2012). Persuasive technologies applicable to the healthcare domain are more effective when personalized based on the user's personal characteristics (Abdullahi, Orji, et al., 2019). In view of the fact that personalized persuasive techniques evoke a different response from more traditional, one-size-fits-all techniques, intervention designers must shift to a more individualized approach guided by the individual's preferences (Abdullahi, Oyibo, et al., 2019).

Personalized interventions that target the nuances that drive user's choices and behaviors are better suited to facilitate effective engagement than black box, one-size-fits-all solutions (Engl et al., 2019). It has been long established that personalized content is more effective as it increases the user's attention, leading to effective engagement (Gena et al., 2019). The application of data collected from individuals is a more advanced method of persuasion that increases the probability of success and results in a more active and effective intervention (Shin & Kim, 2018). Determining what are the key data elements to collect to enhance perceived persuasiveness is critical in the effort to improve engagement (both short and long term).

2.7 Self-Efficacy

Self-efficacy is loosely defined as an individual's belief that he or she is capable of successfully executing courses of action required to successfully produce specific behaviors (Bandura, 1997). An individual's estimate of self-efficacy varies on three dimensions: magnitude (the individual's belief in their ability to complete a task), strength (the individual's confidence that they are capable of completing various components or varying levels of difficulties of a task), and generality (the extent to which an individual's self-efficacy from one task transfers to related tasks) (Bandura, 1997; Bong, 1997). Self-efficacy is regarded as a core premise of human performance, as is demonstrated by its utilization across multiple domains including education (Bulfone et al., 2021; Van Dinther et al., 2013), exercise (Simonavice & Wiggins, 2008), physical activity (Koring et al., 2012), career (Falco & Summers, 2017), and medical (Messina et al., 2018). Bandura (1977) identified four sources of self-efficacy that derive from distinct methods: performance accomplishments (derived from personal experiences of mastering tasks), vicarious experiences (derived from seeing others perform a task successfully), verbal persuasion (derived from leading an individual, through suggestion, to believe he or she can successfully complete a task he or she previously failed), and psychological/emotional arousal (derived from situational sensations experienced by the

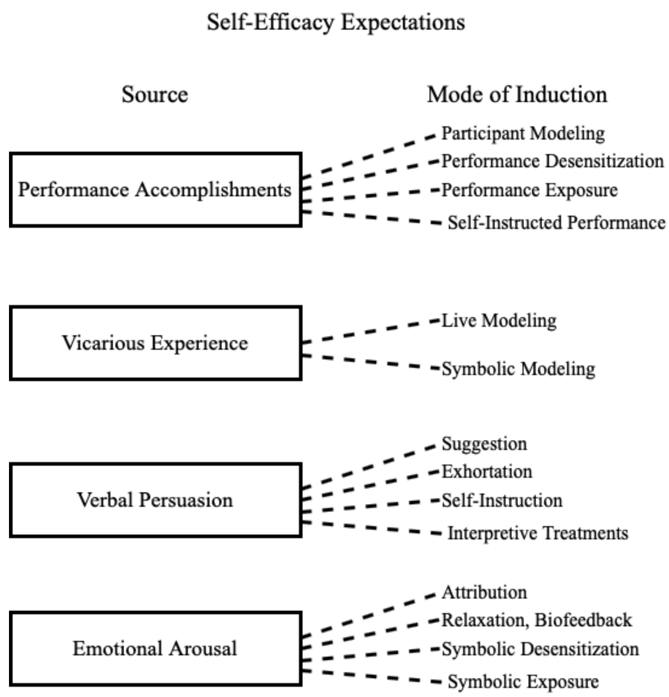

Figure 2. Self-Efficacy and primary sources of induction (Bandura, 1977)

body based on events. These four main constructs of self-efficacy are from multiple modes of input (Figure 2) (Bandura, 1977).

Self-efficacy expectations are developed through the information obtained from the theory's constructs of performance accomplishments, vicarious experience, verbal persuasion, and emotional arousal (Bandura, 1977; Bartley & Ingram, 2017). Performance accomplishments are most closely linked to the individual's past experiences and provide the most direct connection to their ability to succeed (Schunk, 1991; Strauser, 1995; Wallace & Kernozek, 2017). An individual's past success and failure rates raise and lower self-efficacy, respectively (Bandura, 1977). Repeated success leads to high self-efficacy expectations, which sometimes becomes generalized and bleeds over into similar activities (Strauser, 1995). Techniques used to advance performance accomplishments include participant modeling, performance desensitization, performance exposure, and self-instructed performance.

Vicarious experiences are derived from individuals observing others perform a task they consider threatening (Bandura, 1977). Self-efficacy increases as individuals witness a task that is seen as hazardous successfully completed by individuals (Bandura, 1977). As a general rule, vicarious experiences have less impact on an individual's efficacy expectations than direct, personal performance accomplishments (Strauser, 1995). Techniques used to advance vicarious experiences include live modeling and symbolic modeling.

Through verbal persuasion, individuals may be coerced into believing they can successfully complete a task by being told they can succeed (Bandura, 1977). The impact factor of this construct heavily weighs on the ability of the influencer to convince a person that they can succeed (Wallace & Kernozek, 2017). Similar to vicarious experience, verbal persuasion's impact on an individual's self-efficacy than performance accomplishments. While it is typical for an individual to initially experience an increase in self-efficacy as a result of verbal persuasion, any failures the individual may experience will result in a decrease in self-efficacy (Strauser, 1995). Techniques used to advance verbal persuasion include suggestion, exhortation, self-instruction, and interpretive treatments.

Emotional arousal is an individual's assessment of the emotional state they experience when completing a task (McSwiggan & Campbell, 2017). Bandura (1977) postulates that an elevated state of emotional arousal, which is often recognized by an increase in perspiration, an elevated heart rate, etc., is likely to decrease self-efficacy as individuals tend to avoid situations they consider threatening. Situations trigger various emotions that individuals may harvest to gain informative value regarding their level of perceived competency (Bandura, 1977; Strauser, 1995). When emotional arousal is high, attribution, relaxation, biofeedback, symbolic desensitization, and symbolic exposure are methods that are used to decrease emotional arousal and increase self-efficacy.

Individuals avoid tasks they presume to exceed their level of ability (Bandura, 1977). The situations in which these tasks occur affect the individual's evaluation of self-efficacy. Self-efficacy is more likely to be increased when individuals are able to ascribe success as opposed to a failure to their individual skillset (Bandura, 1977; Medrano et al., 2016). The difficulty level of the task also correlates with the individual's appraisal of self-efficacy (Buckworth, 2017). Tasks that are deemed difficult to successfully complete tend to have a negative effect on an individual's appraisal of self-efficacy (Lindenmeier, 2008). According to Bandura (1977), individuals will go so far as to be unwilling to attempt to manage situations where their low self-efficacy indicates a negative outcome (Wigal et al., 1991).

2.8 Adult Hope

The concept of hope is a distinctive phenomenon that spans multiple disciplines such as psychology, theology, philosophy, anthropology, and medicine (Kube et al., 2019). Hope is defined as the motivational frame of mind that is grounded upon the interactivity of an individual's ability to successfully identify ways to achieve a goal (pathway) and their ability to harness the energy to make use of these pathways (agency) (Snyder et al., 1991). Hope is regarded as an important factor in well-being and health that relates to an individual's expectation that he or she will be able to achieve desired outcomes (Nayeri et al., 2020). More extensively, recently qualitative evidence proposes that hope is a motivating factor that contributes to the continuity of a healthy lifestyle (Hollier et al., 2021).

Hope has been found to play a dominant role in everyday life, with higher levels being consistently linked to better outcomes in physical health, academics, and athletics (Balen & Merluzzi, 2021). When compared to individuals with low levels of hope, individuals with high-hope levels have been found to have coping styles that are more adaptive (Edwards et al., 2002). Individuals with high-levels of hope were found to engage in more activities that are designed to enhance his or her health (Redlich-Amirav et al., 2018). Studies have also found higher levels of hope to be connected to better goal setting practices, with hope also being a predictor of better goal outcomes (Moss-Pech et al., 2021).

2.9 Health Consciousness

Consciousness is regarded as the proclivity to adhere to socially prescribed norms that dictate goal-oriented behavior, the willingness to delay gratification, and the ability to control one’s impulses (Costantini et al., 2020). Other facets of consciousness include being responsible, organized, and self-disciplined (Bogg & Roberts, 2013). Individuals with high levels of consciousness are more inclined to align themselves with the conventions associated with conscientiousness (Green et al., 2016). Consciousness has also been shown to positively connect to longevity, and is regarded as a fluid trait that can evolve as a person ages (Roberts et al., 2005). Research has also shown that consciousness influences health through implementation (positive consequences) and inoculation (negative consequences) (Luo & Roberts, 2015).

Health consciousness is defined as the measure to which an individual integrates health concerns into his or her daily regimes (Chen & Lin, 2018; Jayanti & Burns, 1998; Yan et al., 2021). Unlike health motivation, external in nature, health consciousness refers to "how" an individual achieves his or her healthy lifestyle (Jayanti & Burns, 1998). Research has shown that the higher an individual's health consciousness, the more likely they are to adopt a lifestyle grounded in health behaviors such as fitness and nutritional activities (Kraft & Goodell, 1993; Yan et al., 2021). These individuals are cognizant of their health and therefore influenced to adopt these healthier behaviors needed to improve or maintain their health (Barauskaite et al., 2018).

Studies have shown that health consciousness can positively influence engagement in health-oriented actions (Parashar et al., 2019). This motivation to engage in health-oriented actions has the propensity to push an individual to become a connoisseur of health information via media sources such as television (Kraft & Goodell, 1993) and the internet (Ahadzadeh et al., 2018). Also observed has been the correlation between the increase in health consciousness and the increase in preventative healthcare (Donalds & Osei-Bryson, 2020; Jayanti & Burns, 1998). Individuals with high health consciousness reportedly seek to develop and preserve a healthy lifestyle (Park et al., 2017).

2.10 Health Motivation

Health motivation is identified as an individual's drive to engage in health-related activities to improve or maintain preventative health behaviors (Jayanti & Burns, 1998; Tanner et al., 2020). Health motivation has been found to be a relatively consistent state that is deep-rooted in the individual's psychological composition (Jayanti & Burns, 1998). Research has shown that health motivation serves as the source of an individual's desire, adoption, and practice of preventative health behaviors (Jayanti & Burns, 1998; Tanner et al., 2020). Motivation has been found to be both competency-based (whether or not a person can achieve the goal) and goal-oriented (the way a task is managed is determined by the individual's objective (Toste et al., 2020).

It has also been determined that health motivation can gauge an individual's well-being with regard to health behavior-related concerns and actions (Dehghani et al., 2018) and drives consumer engagement in health maintenance behaviors (Tanner et al., 2020). Health motivation is directly linked to an individual's internal characteristics (Jayanti & Burns, 1998). Research has consistently shown that internalized motivation results in more pronounced adherence to preventive health behaviors such as weight loss (Ferron et al., 2010; Ryan & Deci, 2020). Whether or not an individual expects to succeed also plays a key role in their degree of motivation (Muenks et al., 2018). The following section will discuss health consciousness which is closely related to health motivation as it is one of the three elements that comprise health consciousness (Ahadzadeh et al., 2018).

2.11 Personality Traits

Personality traits and the strategies used to engage users have an impact on the effective engagement of the digital health technology (Wagner et al., 2017). Understanding these personality traits are critical to creating digital health solutions that meet the needs of individual user. One of the most commonly used personality models is the Big Five Factor Model (Roccas et al., 2016). The Big Five Factor framework was developed by Lewis Goldberg (1990) and later validated by Costa and McCrae (1992). This model delineates five factors of personality:

1. Openness to experience: the extent to which an individual requires intellectual stimulation, change, and variety
2. Conscientiousness: the extent to which an individual is willing to comply with conventional rules, norms, and standards
3. Extraversion: the extent to which an individual needs attention and social interaction
4. Agreeableness: the extent to which an individual needs pleasant and harmonious relationships with other individuals
5. Neuroticism: the extent to which an individual observes the world as threatening and beyond his or her control (Borghans et al., 2008)

Each Big 5 personality category can be regarded as a continuum where individuals range from high to low (Figure 3).

Frequent time constraints were the driver for a more succinct measurement tool (Gosling et al., 2003). The Mini IPIP scale is a condensed twenty item diagnostic tool that has been validated across multiple studies (Donnellan et al., 2006). Researchers have

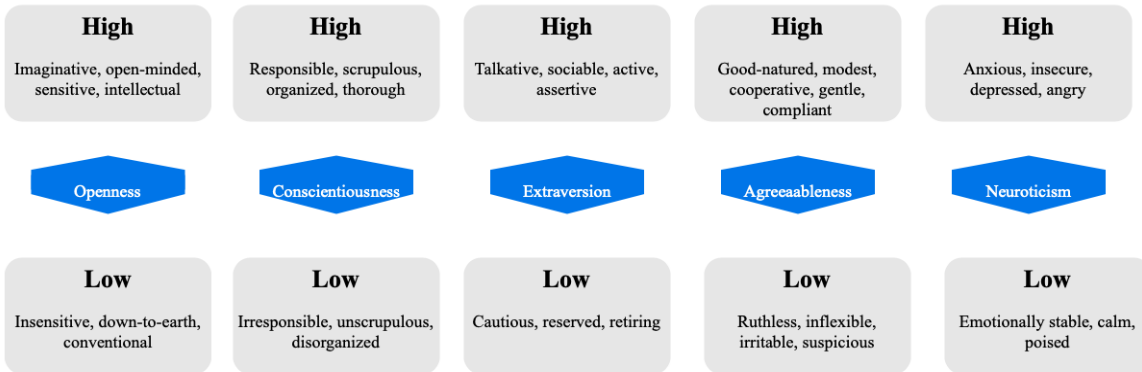

Figure 3. Big 5 Continuum (Roccas et al., 2016)

used the Big 5 framework to predict user characteristics across a conglomerate of domains: career (Wilmot et al., 2019), relationship satisfaction and love styles (White et al., 2004), academic performance (Stajkovic et al., 2018), preventative healthcare (Nolan et al., 2019), and more. More recently, an increasing number of Big 5 studies have utilized machine learning to predict the personality characteristics of users (Bleidorn & Hopwood, 2019).

2.12 Data Science

Data science is the synthesis of contrasting and partially conjoined (sub)disciplines (i.e., statistics, data mining, predictive analytics, behavioral/social science, databases, etc.) (Van der Aalst, 2016). This consolidation of multiple disciplines has led to data science being viewed as the second rendition of statistics. Wu (1997) pushed to move statistics from the standard data collection and analysis focus to an approach that would leverage large, complex datasets to exploit knowledge. Wu (1997) argued that this move gave grounds for statistics to be renamed data science. It was later advocated that the exploration of computing and partnering with professionals from the computing field would be appropriate to expand the statistics field into data science (Cleveland, 2001).

This multidisciplinary field allows data in diverse forms (i.e., big vs small, structured vs unstructured, etc.) to be analyzed and used to provide value. Breiman (2001) advanced that the need to progress from complete dependence on statistical data models to the adoption of more robust and diverse tools such as algorithmic modeling. Data science was later viewed as the intersection of multiple disciplines with statistics playing a foremost role in data science (Dyk et al., 2015). This logic has driven the redirection of the hypothesis testing on small, simple data to hypothesis-free analytical study of large, complex data with the end goal of knowledge discovery and insight (Cao, 2017).

With user engagement being applied increasingly to digital health technologies, the benefits of enhanced outcomes are increasingly informed by mixed method approaches driven by data science (Britt et al., 2020). The use of data science and psychological characteristics has led to remarkable advances in the ability to predict individual differences and similarities (Bleidorn & Hopwood, 2019). The use of data science allows a user's personality to be leveraged to anticipate his or her potential needs (Souri et al., 2018). The field of data science allows researchers to analyze user characteristic data (self-efficacy, motivation, personality traits, etc.) along with aspects of persuasive technology to determine which combinations can be tailored for consumer use.

2.13 Summary

Chapter II established the prevalent problem with persuasive technologies following a one-size-fits-all model in an attempt to effectively engage users. Furthermore, the researcher presented a case that understanding what psychological characteristics drives perceived persuasiveness for an individual lies at the intersection of engagement, persuasive technology, and data science. Although a considerable amount of work has been done toward guiding the creation of engaging one-size-fits-all persuasive technologies, the areas of using data science to drive the creation of dynamic persuasive digital health technologies based on an individual's psychological characteristics are largely unexplored.

To address these shortcomings, we identified a set of psychological assessment tools that will aid digital health technology designers in using data science to develop dynamic persuasive technologies. This research proposes the psychological characteristics measured by examining self-efficacy, health motivation, health consciousness, and personality traits will aid designers in creating dynamic digital health technologies that effectively engage users. Moving beyond conventional methods, data science was utilized as a way to further understand how user characteristics guide their interaction with digital health technologies.

CHAPTER III

STATEMENT OF PURPOSE

The issue with current persuasive design models is that none of the models have addressed psychological characteristics of individual users as summarized in the previous chapter. This creates a flawed design process and leads to potential issues with short and long term engagement (Riley et al., 2011). While digital health technologies are designed to provide assistance to users, they are often designed from a black box, single user perspective resulting in a mismatch between the digital technology and end-user characteristics (Van Velsen et al., 2018; Van Velsen et al., 2013). This archaic approach produces digital health technologies that are crippled at conception and often fail to actively engage users due to the lack of a multidisciplinary approach (Chiasson & Davidson, 2004; Sein et al., 2011). Failing to use a bottom-up design process that considers the individual characteristics of the end-user during the design process often results in a misfit between digital health technology and the user (Keizer et al., 2020). Studies examining the impact of dynamic persuasive digital health technology features on user engagement are a needed step in developing a design science for user engagement (Sundar & Marathe, 2010; Vandelanotte et al., 2016).

Behavioral sciences which seek to understand human activities are becoming more enmeshed in the digital health technology development design process (Hekler et al., 2016; Moller et al., 2017; Rozenfeld, 2018). Identifying the most effective persuasive technology design principle is not an acceptable starting point anymore (Morrison et al., 2012). Designers must address the multifaceted topography of user characteristics in order for digital health persuasive systems to successfully engage users (Krebs et al., 2010; Van Gemert-Pijnen et al., 2011). The fallacy of Argumentum Ad Populum ("appeal to the majority") is commonly used in the persuasive technology realm (Anagnostopoulou et al., 2018; Orji & Mandryk, 2014). One-size-fits-all methods which seek to accommodate the majority often result in the degradation of the effectiveness of interventions (Kelders et al., 2012). By seeking to understand the nuances of this interdisciplinary field, developers of persuasive digital health technologies are able to address the dynamic person-based needs of intervention users that must be addressed (Riley, 2017; Russell, 2011; Yardley et al., 2015).

Persuasive technology features become obsolete over time because designers do not address the multivariate, dynamic characteristics of mHealth app users (Oinas-Kukkonen, 2018). Given the flawed nature of the design process, to leverage the benefits of successfully engaging the users of digital health technologies, it is desirable that dynamic features driven by user characteristics are amalgamated into the design process to better serve the context of user engagement (Naslund et al., 2017; Spruijt-Metz & Nilsen, 2014). A methodical approach which intersects dynamic data driven design facilitated by persuasive technology will allow researchers and designers of persuasive technologies to predict the persuasive features that will successfully engage users, thus enabling effective engagement. This research is guided by broadening the PSD framework, based on the use of psychological characteristics to address the dynamic needs of the users of digital health technologies.

3.1 Specific Aims and Hypotheses

The purpose of this research is outlined through the following specific aims and hypotheses:

3.1.1 Specific Aim 1

Specific Aim 1: Determine how psychological characteristics impact perceived persuasiveness.

Rationale: Previous research has identified a deficiency in PSD frameworks which fail to incorporate a user-centric model dynamically driven by the psychological characteristics of digital health technology users. Individual users' characteristics may have an impact on perceived persuasiveness (Ciocarlan et al., 2019). Dynamic data-driven making capabilities are important to designers of persuasive technologies as they will fill the gap created by one size fits all approaches (F. A. Orji et al., 2019).

Users that lack motivation or feel incapable of executing tasks will not engage with mHealth apps (Buckworth, 2017; Hung et al., 2017).

Hypothesis 1: Self-Efficacy will positively influence interpreted mHealth screen perceived persuasiveness.

Hope has been positively associated preventative behaviors such as engaging in physical behavior (Balen & Merluzzi, 2021).

Hypothesis 2: Adult hope will positively influence interpreted mHealth screen perceived persuasiveness.

Highly motivated individuals who feel they are able to execute health related tasks are more likely to be conscientious about their health and more willing to use mHealth (Chen & Lin, 2018; Redlich-Amirav et al., 2018).

Hypothesis 3: Health Consciousness will positively influence interpreted mHealth screen perceived persuasiveness.

Hypothesis 4: Health Motivation will positively influence interpreted mHealth screen perceived persuasiveness.

Individual personality traits often not only reflect what drives and motivate people, but also what they prefer. The Big 5 personality dimensions describe groups human behavior into five dimensions: Openness, Conscientiousness, Extraversion/Introversion, Agreeableness/Disagreeableness, and Neuroticism. Individual personality traits should be an antecedent of consumer engagement with mHealth apps (Gosling et al., 2003).

Hypothesis 5: Openness will positively influence interpreted mHealth screen perceived persuasiveness.

Hypothesis 6: Conscientiousness will positively influence interpreted mHealth screen perceived persuasiveness.

Hypothesis 7: Extraversion will positively influence interpreted mHealth screen perceived persuasiveness.

Hypothesis 8: Agreeableness will positively influence interpreted mHealth screen perceived persuasiveness.

Hypothesis 9: Neuroticism will negatively influence interpreted mHealth screen perceived persuasiveness.

3.1.2 Specific Aim 2

Specific Aim 2: Evaluate the survey data utilizing contrast mining to determine the combination of psychological characteristics and persuasive principles that lead to enhanced perceived persuasion.

Rationale: Current PSD frameworks fail to systematically incorporate data driven decisions into the design of digital health technologies. Contrast mining can identify the significant personality characteristic differences that may lead to enhanced persuasiveness among groups of users and patients. By using this information, designers of digital health technologies can establish enhanced guidelines for the conceptualization of personalized persuasive intervention design for a given group; this, in turn, would lead to improved engagement of users. The recognition of additional differences will in turn allow designers of digital health technologies to better engage users and establish guidelines in each user/patient group which would help in the conceptualization of a personalized persuasive intervention design.

CHAPTER IV

METHODOLOGY

This chapter outlines the methods used to test the data science approaches described in Chapter III. The chapter will first describe the mHealth app questionnaire development which included: creation and validation of mHealth screens, the validated measures used, participant sampling, overall survey flow, the statistical analysis method, and the contrast pattern data mining approach that will be used to investigate the survey data.

4.1 Questionnaire Development

To examine what factors were related to engagement behavior with intention to use a mHealth application, a multiple-phase experiment was conducted during the Summer 2020. This experiment involved a survey-based design with a series of 25 mHealth app screens that featured the use of persuasive principles with a focus on physical activity. The IRB approval forms for this survey are included in Appendix A.

4.2 mHealth Screen Development and Validation

To examine the perceived persuasiveness of the mHealth screens, twenty-five unique mHealth screens were developed following the PSD categories and principles developed by Oinas-Kukkonen and Harjumaa (2009). The screens were all developed with a central theme of improving/increasing exercise as a use case.

The mHealth screen development process began by creating a wireframe prototype (Rosenzweig, 2015). The prototype was created on sheets of paper, with each sheet representing one of the mobile health app screens. The initial step for each prototype was to document the persuasive system category, the design principle, and the design principle requirement per Oinas-Kukkonen. A brief write-up of the details of the screen was then added to the prototype, followed by the mHealth screen being given a reference name based on the detail in the writeup that was used throughout the questionnaire development and analysis process. A sketch of the prototype was then drawn based on the documentation so that each sheet would represent one of the mHealth screens.

Next, BuildFire (2019) was used to develop a digital high-fidelity prototype for each mobile app screen. These prototypes were used to support the design goals established during the initial prototype. Once the prototypes were developed, an iPhone XS Max was then used to create still images of the mHealth screens using the screenshot function. This method was utilized so the image would visually represent what a user would see on their cellphone. The images were then exported from the phone to a laptop via email. Once the prototypes were exported, two experts in the field of persuasive technology conducted a blind review to validate the mHealth screen represented the persuasive technology principle intended by the author. The expert review panel consisted of n=1 reviewer with 12 years in the persuasive technology field and n=1 reviewer with 9 years in the persuasive technology field.

Following the expert inspection and blind review, a consultation was held with the expert review panel where notes and suggestions were reviewed. The review and modification process continued until the developer and reviewers reached a consensus. The mHealth screens were iteratively evaluated, modified, and improved following each expert inspection and blind review. For the first round, twenty-three mHealth screens were developed: Add, Start, Burpee-Squat, Increase, Mountain, Target, Trophy, Late, Calories, Dinner Chat, Tracker, About Us, Stories, Leaderboard, Journal, Partners, Ads, Strategy, CDC, HIPAA, Contact, Before After, and Yoga. The developer and reviewers identified eleven mHealth screens with conflicting persuasive technology principles that required modification: Target, Dinner Chat, About Us, Journal, Partners, Strategy, HIPAA, Contact, Before After, Yoga, and CDC. CDC was dropped during the first round because the designed persuasive category was not seen by either of the two reviewers and the category that was identified was seen in another screen. The Apple mHealth screen was created to replace CDC and submitted with revisions for round 2. A consensus was reached on the twenty-three mHealth screens during the second round. Additionally, three paper and high-fidelity prototypes were created for the remaining mHealth screens (SSL, Avatar, and Recreation) following the methods stated above. The additional mHealth screens were iteratively evaluated, modified, and improved using expert inspection and blind review methods used during rounds one and two. The iterative process resulted in twenty-five mHealth screens designed for the questionnaire that were agreed upon through the blind review process and one mHealth screen prototype being discarded. The mHealth screen acceptance by round is shown in Table 1.

Table 1. mHealth Screen Acceptance by Round

Screen Name	Round 1	Round 2	Round 3
Add	X		
Start	X		
Burpee-Squat	X		
Increase	X		
Mountain	X		
Target		X	
Trophy	X		
Late	X		
Calories	X		
Dinner Chat		X	
Tracker	X		
About Us		X	
Stories	X		
Leaderboard	X		
Journal		X	
Partners		X	
Ads	X		
Strategy		X	
CDC	Dropped	N/A	N/A
HIPAA		X	
Contact		X	
Before After		X	
Yoga		X	
Apple	N/A	Replaced CDC	
SSL	N/A	N/A	X
Avatar	N/A	N/A	X
Recreation	N/A	N/A	X

The primary task support category aids the user in performing fundamental tasks by reducing complex tasks into simpler tasks. Primary task principles include reduction, tunneling, tailoring, personalization, self-monitoring, simulation, and rehearsal (Oinas-Kukkonen & Harjumaa, 2009). Table 2 describes the primary task support design principles.

Table 2. Primary Task Principles (Oinas-Kukkonen & Harjumaa, 2009)

Persuasive System Category	Design Principle	Principle Description
Primary Task Support	Reduction	Provides simple steps for an activity
	Tunneling	Guides people in a process step by step to meet a goal
	Tailoring	Uses factors relevant to the individual to motivate the users based on their needs, interests, personality, etc.
	Personalization	Suggestions, praise, and rewards are given at appropriate time to motivate users to stay on track
	Self-Monitoring	Allows users to follow/monitor their performance to make sure they're staying on track
	Simulation	Allows the user to observe the cause-and-effect link regarding his/her behavior
	Rehearsal	Allows users to rehearse a behavior

The dialogue support category facilitates human to computer dialogue between the persuasive system and the user. The principles that are used to provide feedback are praise, rewards, reminders, suggestion, similarity, liking, and social role (Oinas-Kukkonen & Harjumaa, 2009). Table 3 describes the principles in the dialogue support category.

The system credibility category represents how to make systems more persuasive by making them more credible. The principles that are used to give credibility include trustworthiness, expertise, surface credibility, real-world feel, authority, third-party endorsements, and verifiability (Oinas-Kukkonen & Harjumaa, 2009). Table 4 describes the principles in the system credibility category.

Principles in the social support category motivate systems through the use of

Table 3. Dialogue Support Principles (Oinas-Kukkonen & Harjumaa, 2009)

Persuasive System Category	Design Principle	Principle Description
Dialogue Support	Praise	Uses images, words, sounds, etc. to praise the user for his/her behavior
	Rewards	Uses virtual rewards the user for performing tasks related to the target behavior
	Reminders	Reminds the user of his/her target behavior
	Suggestion	Offers the user suggestions that fit the target behavior
	Similarity	Remind users of themselves in some way
	Liking	The digital health technology should be visually attractive
	Social Role	The digital health technology adopts a social role

social influence. The design principles in this category include social facilitation, social comparison, normative influence, social learning, cooperation, competition, and recognition (Oinas-Kukkonen & Harjumaa, 2009). Table 5 describes the social support principles.

Table 6 depicts the final iteration of testing and includes the principles per screen and the principle category (PT = primary task support, DS = dialogue support, SC = system credibility support and SS = social support). Figure 4 shows one of the final mHealth screens that was developed. A visual representation of all 25 screens is available in Appendix J. Of the 25 screens that were developed, 5 screens have a primary principle from the primary task support category, 7 screens have a primary principle from the dialogue support category, 8 screens have a primary principle from system credibility

Table 4. System Credibility Principles (Oinas-Kukkonen & Harjumaa, 2009)

Persuasive System Category	Design Principle	Principle Description
System Credibility Support	Trustworthiness	Applications should appear to be truthful, fair, and unbiased
	Expertise	Provide content from sources that are knowledgeable and competent
	Surface Credibility	Systems should visually appear to be competent and credible
	Real-world Feel	Systems should highlight the people or organizations that are providing content by providing information about them
	Authority	Systems should leverage roles of authority by referring to organizational and people that are seen as authority figures
	Third-party Endorsements	Systems should provide users with endorsements from third parties that are well-known and trusted
	Verifiability	Systems should provide ways for users to easily use outside sources to verify the accuracy of the content

support category, and 5 screens have a primary principle from the social support category. Figure 5 shows the percentage of screens by primary persuasive technology category.

<u>4.3 Measurement Items</u>

Psychological characteristics were assessed with a variety of validated scales. Measurement items utilized in the current study evaluated the participant's degree of self-efficacy, hope, health consciousness, health motivation, and their personality traits. Perceived persuasiveness, intention, and willingness to use we assessed at the screen

Table 5. Social Support Principles (Oinas-Kukkonen & Harjumaa, 2009)

Persuasive System Category	Design Principle	Principle Description
Social Support	Social Learning	The digital health technology should target behavior by providing the user with a way to observe other users who are performing the same target behavior
	Social Comparison	The digital health technology should motivate the user by allowing them to compare his/her performance to other users that are performing the same task
	Normative Influence	The digital health technology should use normative influence/peer pressure
	Social Facilitation	The digital health technology should allow users to perceive that other users are using the system to perform the target behavior along with them
	Cooperation	The digital health technology should leverage the users natural drive to co-operate
	Competition	The digital health technology should leverage the users natural drive to compete with other users
	Recognition	The digital health technology should offer users public recognition

level using validated scales, Measurements used in this study will be described in the following five sections.

4.3.1 Self-Efficacy

After completion of the social demographic information the participants were asked eight questions about their self-efficacy utilizing Chen et al.'s (2016) New General Self-Efficacy scale (see Appendix B). Chen et al.'s (2016) work extends Bandura's (1977, 1997) work which focused on the magnitude and strength dimensions of self-efficacy and includes the generality dimension of self-efficacy. This section presented

Table 6. Mobile App Screen Name with Persuasive Principles and Categories

Screen Name	Principle 1 (Primary)	Principle 2	Principle 3
Add	(PT) Tailoring	(PT) Tunneling	
Start	(PT) Reduction	(PT) Tunneling	
Burpee-Squat	(PT) Tunneling	(PT) Reduction	
Increase	(DS) Praise		
Mountain	(PT) Rehearsal	(DS) Suggestion	
Target	(DS) Praise	(PT) Personalization	
Trophy	(DS) Rewards	(DS) Praise	
Late	(DS) Reminders		
Calories	(DS) Suggestion		
Dinner Chat	(DS) Social Role	(DS) Praise	
Tracker	(PT) Self-Monitoring		
About Us	(SC) Expertise	(SC) Trustworthiness	(SC) Authority
Stories	(SS) Recognition	(PT) Simulation	(DS) Praise
Leaderboard	(SS) Competition		
Journal	(SS) Social Learning	(SS) Social Comparison	(SC) Social Facilitation
Partners	(SC) Trustworthiness	(SC) Expertise	(SC) Authority
Ads	(SC) Surface Credibility		
Strategy	(SC) Authority	(SC) Expertise	
Apple	(SC) Verifiability	(SC) Expertise	(SC) Authority
HIPAA	(SC) Trustworthiness	(SC) Surface Credibility	
Contact	(SC) Real-World Feel		
Before After	(SC) Normative Influence	(PT) Simulation	
Yoga	(SS) Cooperation	(DS) Praise	(SS) Social Comparison
SSL	(SC) Third-party Endorsements	(SC) Trustworthiness	
Avatar	(DS) Similarity	(DS) Liking	

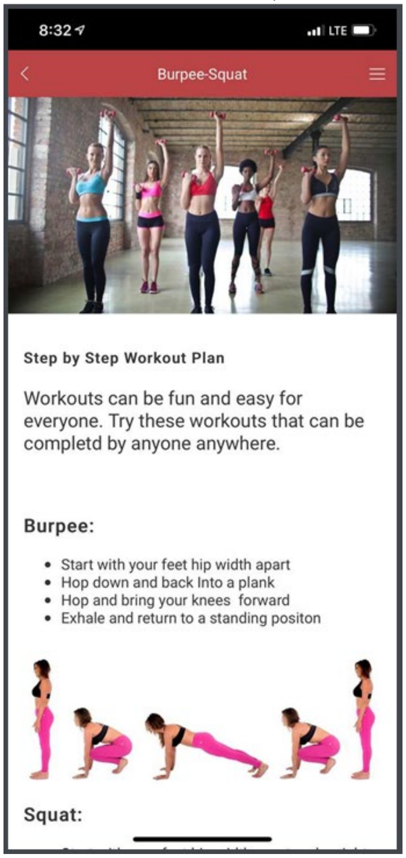

Figure 4. Sample mHealth Screen developed and accepted during review

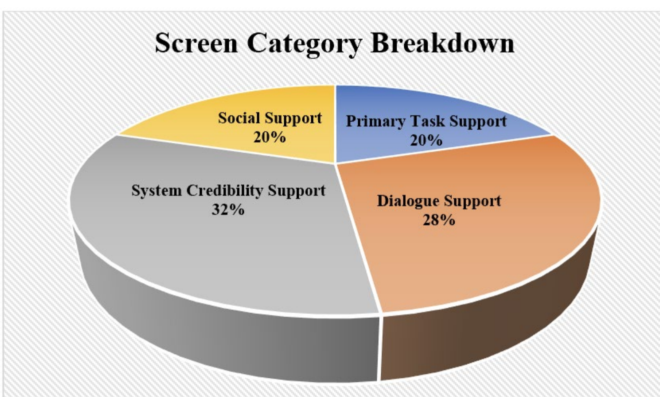

Figure 5. Mobile Screen Primary Category Percentage

participants with statements such as: “I will be able to achieve most of the health goals that I have set for myself” and “In general, I think that I can obtain health outcomes that are important to me”. The participants answered the eight questions using a 7-point Likert scale ranging from strongly disagree to strongly agree.

4.3.2 Adult Hope Scale

Participants were then asked about their overall hope utilizing Snyder et al.’s (2007) Adult Hope Scale (see Appendix C). This section consisted of eight questions utilizing a 7-point Likert scale ranging from definitely false to mostly true. Participants answered questions about their overall hope such as: “I can think of many ways to get out of a jam” and “I can think of many ways to get the things in life that are important to me.”

4.3.3 Health Consciousness

Participants were then asked to complete six questions about their health consciousness utilizing Jayanti and Burns’s (1998) Health Consciousness scale (see Appendix D) which is adapted from Kraft and Goodell’s (1993) original Health Consciousness scale. The seven-item Likert scale used in this study ranged from strongly disagree to strongly agree. Types of health consciousness questions the participants encountered include: “I am interested in information about my health” and “I read more health-related articles than I did 3 years ago”.

4.3.4 Health Motivation

Participants were then asked to complete questions about their health motivation utilizing Jayanti and Burns’s (1998) Health Motivation scale (see Appendix E). This section consisted of six questions utilizing a seven-point Likert scale which ranged from strongly disagree to strongly agree. Participants answered questions about their health motivation such as: “I try to prevent common health problems before I feel any symptoms” and “I would rather enjoy life than try to make sure I am not exposing myself to health risks.”

4.3.5 Personality Traits

Finally, participants were asked to answer personality questions that generally describe them as they are now and not as they wish to be in the future. The participants completed Donnellan et al.’s (2006) Mini-IPIP scale (see Appendix F) which consists of 20 questions with a focus on extraversion, agreeableness, conscientiousness, neuroticism and intellect/imagination. The questions were answered using a 7-point Likert scale ranging from extremely inaccurate to extremely accurate. Participants rated the accuracy of statements such as: “Am the life of the party” and “Am not really interested in others”.

4.3.6 Perceived Persuasiveness

After answering psychological questions, the participants were asked to complete questions about the perceived persuasiveness of the individual mHealth screens. The participants completed Lehto et al.’s (2012) Perceived Persuasiveness scale (see Appendix G) which consists of three questions utilizing a seven-point Likert scale which ranged from strongly disagree to strongly agree. Participants answered questions, at the screen level, about the perceived persuasiveness of the mHealth app screens such as: “This mobile health screen has an influence on me” and “This mobile health screen makes me reconsider my overall health and wellness.”

4.3.7 Intention

Participants were then asked about their intention to use the individual mHealth screens predicated on the assumption that he or she has access to it. Intention was measured using Venkatesh et al.'s (2008) Intention scale (see Appendix H) which consists of three questions utilizing a seven-point Likert scale which ranged from strongly disagree to strongly agree. Participants answered questions such as: "Assuming I had access to the mobile health app, I intend to use it" and "Given that I had access to the mobile health app, I predict that I would use it."

4.3.8 Willingness to Use

Finally, participants were asked questions related to their willingness to utilize the individual mHealth apps. Willingness was measured using Sittig et al.'s (2020) Willingness to Use scale (see Appendix I) which utilizes a seven-point Likert scale ranging from strongly disagree to strongly agree. Participants answered questions about their willingness to use the individual mHealth apps such as "How willing are you to use this type of mobile healthcare app to help you improve your overall health" and "How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?"

4.4 Sample

Participants were recruited by Qualtrics to use the XM Research Service's online survey system (Qualtrics, 2019), which has been used previously by researchers in a variety of disciples (Kniffin et al., 2019; Pangbourne et al., 2020). Qualtrics reimbursed participants a predetermined amount that was arranged between Qualtrics and the participant. Once the interested participants were selected by Qualtrics, they were directed to the informed consent page via an anonymous link. Upon consenting to participate, they were directed to the online Engagement Screen Survey (see Appendix J). Participants were recruited from July 23, 2020, through August 3, 2020. The majority of participants (92%) completed the questionnaire during the final week. The Engagement Screen survey took an average of 28.082 minutes to complete. There were 273 completed survey responses however 11 were deleted due to evident signs of respondents being "speeders" that completed the survey in an impossibly quick time or "straight lining" and giving identical answer choices repeatedly, leaving the present study with 262 viable responses. 232 (83.75%) of the respondents reported that their race was Caucasian. Race was not representative of the population and was dropped from future analysis.

4.5 Control Variables

Using an approach similar to Orji (2014) and Schuz (2017) participants were asked demographic information about their gender, age, ethnicity, and educational level. Orji proposed that gender played an influential role on the effects of perceived persuasiveness on applications promoting health behavior. Recognizing that health disparities often exist across socio-economic groups, Schuz (2017) proposed factors contributing to socio-economic characteristics (i.e., ethnicity, education level, age) could be better integrated in research of health behaviors. Controlling for these variables provides a clearer understanding of how much the unique variance of each of the independent variables is contributing to the perceived persuasiveness of the mobile health screens. Demographic details are provided in Table 7.

Table 7. Consumer Health Engagement Screen Survey Participant Demographics

Gender	Frequency	Percentage
Male	122	46.6%
Female	138	52.7%
Other	2	0.8%
Age Range		
Under 40	57	21.8%
40-59	60	22.9%
60 and Older	145	55.3%
Ethnicity		
White	219	83.6%
Black or African American	12	4.60%
American Indian or Alaska Native	1	0.4%
Asian	17	6.5%
Hispanic or Latino	9	3.40%
Other	4	1.5%
Level of Education		
Less than high school degree	6	2.30%
High school graduate (diploma or equivalent)	38	14.50%
Some college but no degree	59	22.50%
Associate degree in college (2-year)	32	12.20%
Bachelor's degree in college (4-year)	63	24.0%
Graduate’s degree	64	24.40%
Total	N= 262	

4.6 Data Science Analysis

IBM SPSS version 27 (2020) was used to conduct tests for normality, order effect, descriptive statistics, exploratory factor analysis, and multiple linear regressions. Contrast pattern data mining was used to investigate patterns to identify combinations of persuasive principles. Contrast, the publicly available Python implementation of Search and Testing for Understandable Consistent Contrasts (STUCCO) algorithm developed by Hosseini (2018) was used to find differences between contrasting groups.

4.6.1 Statistical Approach

Gaps and limitations are present within the existing literature for developers of persuasive technologies utilizing PSD frameworks. Based on these deficiencies within the research, the current project presents multiple stated aims and hypotheses. Nine hypotheses are stated to determine the effects of psychological characteristics on mHealth screen perceived persuasiveness. Multiple linear regressions will be used to offer statistical evidence of the effects of psychological traits on perceived persuasiveness. Correlational design will be used to determine the contribution of the four independent variables (self-efficacy, health consciousness, health motivation, and personality traits) on the dependent variable (perceived persuasiveness).

4.6.1.1 Exploratory Factor Analysis (EFA).

Exploratory Factor Analysis (EFA) is an essential statistical instrument that is used by researchers to refine measures, evaluate the validity of constructs, and test hypotheses (Conway & Huffcutt, 2016). Researchers often use EFA for preliminary purposes to determine the least number of constructs needed to reproduce the original data with no covariance (Gorsuch, 1997). This widely used method is extremely versatile as it permits researchers multiple extraction models (i.e., principal components vs common factors), multiple criteria selection options when determining which factors to retain (i.e., eigen values greater than 1.0 vs scree test), and multiple rotation options (i.e., orthogonal vs oblique). Domains such as social sciences permit some degree of correlation between factors because of the acknowledgement that behavior does not function independently (Costello & Osborne, 2005). Arguably oblique rotations allow factors to correlate and prevent valuable information from being loss due to covariances therefore producing a more accurate and reproducible solution. For the measurement items in this study, EFA was conducted using a Promax rotation in SPSS 27.

4.6.1.2 Multiple Linear Regression.

Multiple Linear Regression (MLR), a term used to describe a highly adaptable data-analytics system whose usage has emerged in the behavioral and biological sciences because of its usefulness to researchers seeking to examine the covariance of variables as a function of factors of interest (Cohen et al., 2003). These techniques allow the relationship, the reason, and result relationship between single or multiple independent (predictor) variables and a single dependent (criterion) variables to be explored (Uyanık & Güler, 2013). Similar to other multivariate statistical techniques, MLR makes the assumption of linearity, normality, a constant error variance (homoscedasticity), independent of errors (no correlation between errors among independent variables) (Hair et al., 2019).

The A-priori Sample Size Calculator for Multiple Regression was used to calculate the minimum sample size need to achieve statistical results (Soper, 2021). A-priori values of an anticipated effect size f^2 equal to 0.02 which is considered small, desired statistical power equal to 0.8 which is considered appropriate, predictor variables equal to 1, and the significance level set to 0.05 which is statistically significant. Using these values, a minimum sample size of 385 at the mHealth screen level is required to analyze perceived persuasiveness data with sufficient statistical power.

4.6.1.3 Common Method Bias.

Common Method Bias is the discrepancy between the actual and observed relationships between constructs (Doty & Glick, 2016). The impact of Common Method Bias has been highly debated. Common Method Bias occurs when all the data (i.e., dependent variables, independent variables, etc.) are all collected via the same method. Common approaches to detect Common Method Bias are Harman's one factor model, Confirmatory factor analysis (CFA), and the unmeasured latent marker construct (Schwarz et al., 2017).

Strategies used to reduce Common Method Bias include improving scale item clarity by refraining from using ambiguous terms such as "occasionally" or "somewhat", statistical methods such as exploratory factor analysis (EFA) which uses cross loading of constructs to indicate common method bias, and marker variables (Jordan & Troth, 2019). Randomizing items within your method is also a procedural solution for Common Method Bias (MacKenzie & Podsakoff, 2012). Each of these strategies is utilized in this study.

4.6.1.3.1 Marker Variable. When using the marker variable (MV) technique, the researcher includes a variable that is distinct and unrelated to other variables in the model (Lindell & Whitney, 2001). The marker variable technique has proven to be very effective and highly flexible (Craighead et al., 2011). The a priori assumption is that there should be no correlation between the marker variable and the other unrelated variables in the model. This study consisted of four marker variable questions which used a scale ranging from strongly disagree to strongly agree. Participants answered questions related to the color silver such as: “I prefer silver to other colors” and “I like the color silver”.

4.6.1.3.2 Attention Factor. Attention checks are used to improve data quality by verifying the respondent is attentively reading the survey items he or she is responding to (Alvarez et al., 2019; Kung et al., 2018). Embedded directed queries were used for the attention factor. This type of attention check instructs respondents to answer questions in a specific manner (Abbey & Meloy, 2017). Participants that did not give the exact response as prompted were removed from the study. The attention factor questions were dispersed throughout the section of the survey that was related to the mobile health screens, for a total of thirteen attention checks. An incorrect response is a clear signal that the respondent is not paying attention and the response should be discarded.

4.6.2 Contrast Mining Approach

Aim 2 seeks to extract significant differences between groups of users based on the interrelationships of combinations of persuasive principles, psychological characteristics (i.e., self-efficacy, health consciousness, health motivation, and extraversion), and demographic variables. Demographic variables that will be assessed include age, gender, and education. Building on Orji (2014) and Schuz’s (2017) approach, combinations of age and gender will be examined to further explore Orji’s (2014) proposal regarding the impact of gender on perceived persuasiveness. Age and education level will be combined in an effort to further explore Schuz’s (2017) argument for the factors contributing to socio-economic characteristics to be integrated in health behavior research.

Contrast Set Mining (CSM), a subclass of data mining, will be used to assess the correlations among the combinations of primary persuasive system categories, psychological characteristics, perceived persuasiveness, and demographic groups. CSM finds differences in datasets or groups that are statistically meaningful. This work will use Contrast (Hosseini, 2018), which is a publicly available Python implementation of the Search and Testing for Understandable Consistent Contrasts (STUCCO) algorithm. The contrast mining experiment will use VMWare Fusion version 12.1.2 running on an Apple MacBook Pro with an Intel(R) Core (TM) i7-8559U CPU @ 2.70 GHz 2.71GHz and 16 GB RAM. The virtual machine is a Windows 10 Education 64-bit (Version 1909, Build 18363.2037) and 8.00 GB RAM. Microsoft Excel for Microsoft 365 MSO (Version 2201 Build 16.0.14827.20198) 64-bit will be used to create the data files. Python 3.9.7 running in Jupyter Notebook version 6.4.5 will used for data analysis. Pandas framework version 1.3.4 and NumPy framework version 1.20.3 will be used for data processing, data analysis, and data visualization.

4.6.2.1 Contrast Mining.

Contrast mining is a subarea of data mining that focuses on finding contrasting patterns that express significant differences in multiple datasets or classes, often comparing cases with a desired outcome against those with an undesired outcome (Dong & Bailey, 2012). Understanding the key differences between datasets is a fundamental data mining endeavor in data analysis (Bay & Pazzani, 2001a). Previous studies have used an abundance of terms to describe contrast mining, including emerging patterns, group differences, classification rules, and discriminating patterns (Dong & Bailey, 2011). Contrast pattern based mining provides a unique angle and has been applied by researchers to problems in data analysis diverse areas (Dong & Bailey, 2012).

Pattern trees are frequently used in contrast mining algorithms to discover significant differences in datasets. A pattern tree is a data mining method that uses tree branches to determine potential outcomes. Each individual branch of the pattern tree can be regarded as a pattern from the data. This method of pattern generation often results in a large number of rules that refer to small sets being generated (Mehrotra et al., 2016), leaving the user to determine importance. Figure 6 depicts a sample pattern tree. Commonly used tree structure ordering includes frequent tree ordering where single items in the dataset are ordered in accordance with their frequency, difference ordering where items are sorted according to their frequency (also referred to as support) with contrast sets with higher support initially being placed higher in the tree, and hybrid ordering which combines the two methods where items are chosen using difference ordering and according to their frequency (Ventura & Luna, 2018). Multiple contrast pattern based mining algorithms have been proposed in the literature STUCCO (Bay & Pazzani, 1999), Contrasting Grouped Association Rules (CIGAR) (Hilderman & Peckham, 2007), and Contrast Set Mining—Subgroup Discovery (CSM-SD) (Kralj Novak et al., 2009). Contrast learning is exceptionally versatile and has been used in supervised and unsupervised learning, exploratory analysis, and outlier detection (Savage et al., 2017).

Progress in the data analysis and digital health technologies domain have given rise to unprecedented opportunities to monitor, evaluate, and change health practices, thereby accelerating the ability to understand and influence health behaviors and outcomes (Marsch, 2021). Data-mining methods provide researchers the ability to investigate patterns in the data gathered from digital health technologies and validate the credibility of their results. Even though contrast mining techniques in the health domain (especially consumer health informatics) are still relatively new, it holds great promise to further understand consumers' interaction with digital health solutions to improve their overall health. STUCCO was selected because unlike other statistically based algorithms, it tests multiple hypothesis efficiently by implementing a tree search method (Qian et al., 2020).

4.6.2.2 Contrast: A Mining Algorithm.

As a result of EFA Analysis, a substantial portion of the data are in continuous data types. The continuous data types are referred to as weighted values. These values represent final calculations that take into account that items in the scale do not equally contribute to the average. The database is separated into three Pandas data frames. All three data frames will include the following attributes: Primary Category, Self-Efficacy Weighted, Health Consciousness Weighted, Extraversion Weighted, Health Motivation Weighted, and Perceived Persuasiveness Weighted. The difference between the three data frames is the addition of Gender, Age_R,Education_R; Age_Gender_Combined (A_G C); and Age_Education_Combined (A_E C) respectively. Table 8 provides the attributes of the modified survey data that were used for contrast pattern analysis and the corresponding data type. The STUCCO algorithm, including the software implementation of Contrast, relies on a discretization method which bins the values by creating discrete intervals (Dong & Bailey, 2012). The term contrast set represents the differences among groups. Contrast sets are combinations of attributes from the database.

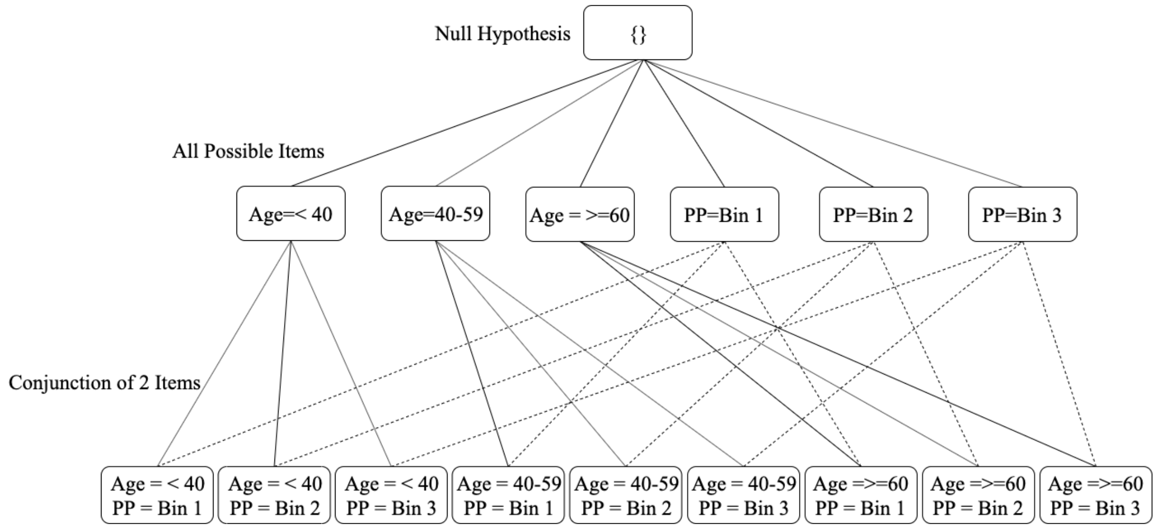

Figure 6. Sample Decision Tree

Table 8. Sample Dataset Record

Attribute	Explanation	Type
Primary Category	Primary Persuasive Technology Category	String
Self-Efficacy Weighted	Weighted Self-Efficacy Score	Continuous
Health Consciousness Weighted	Weighted Health Consciousness Score	Continuous
Extraversion Weighted	Weighted Big 5 Extraversion Score	Continuous
Health Motivation Weighted	Weighted Health Motivation Score	Continuous
Perceived Persuasiveness Weighted	Weighted Perceived Persuasiveness Score	Continuous
Gender	Survey Participant's Gender	Category
Age_R	Age Group of the Survey Participant	String
Education_R	Education Level of the Participant	String
Age_Gender_Combined	Value Representing the Age Group and Gender Combination of the Survey Participant	Category
Age_Education_Combined	Value Representing the Age Group and Education Level Combination of the Survey Participant	Category

Contrast deviates from the original STUCCO implementation in the manner that support is calculated. Association rule support, which checks to see if there is a difference between groups, is calculated for minimum support (Hosseini, 2018). Code modifications were made to the Contrast algorithm so that it more properly aligned in the contrast mining realm. The minimum support that was being calculated was replaced with the proper contrast support which is the percentage that the rule is true (Bay & Pazzani, 2001b). The Contrast implementation also controls for errors by automatically eliminating rules that appear less than ten times in the data set. Our implementation skipped the pruning and size effects that were integrated in the Contrast code, instead we calculated minimum support and generated all possible contrast sets. These additional controls will be added in future revisions. Table 9 lists the calculations that were utilized in this study.

Contrast allows minimum thresholds to be set to guide the accuracy of the scoring function. Minimum values were entered for lift, association support, and the maximum confidence. This research considerers rules with lift values that are greater than 1.05 and association support values greater than the minimum support threshold of 1.0% significant. Given that the primary category of 20% of the screens are from primary task support, 28% are from dialogue support, 32% are from system credibility support, and 20% are from social support, the minimum confidence needs to be set higher than these values to account for random selection. The rule is considered significant if the maximum confidence is greater than 33%.

4.7 Summary

This chapter described the data collection methods and the proposed processes for developing the instrument related to the current study. Experimental manipulations involving the content of the survey, as well as a description of the process and format were explained.

Table 9. Contrast Mining Algorithm Terms and Definitions

Term	Definition
Lift	Determines if the rule is happening more than chance. Values above 1 indicate the rule isn't happening by chance.
Association Support (asc supp)	The percentage of time the given rule appears in the entire database.
Support Rule	Synonymous with rule_support. The percentage of time the rule appears in the given group.
Maximum Support of the Opposing Group (max supp of Opposing Group)	Of the remaining groups, the maximum "rule_support "achieved by another single group.
Minimum Support of the Opposing Group (min supp of Opposing Group	Of the remaining groups, what is the minimum "rule_support" achieved by another single group.
Maximum Absolute Difference in Contrast Support (Max Abs Diff In Contrast Supp)	The maximum value of the difference between the maximum support of the opposing group and the support rule and the difference between the minimum support of the opposing group and the support rule. Max(Max Support of Opp Group - Support Rule, Min Support of Opp Group - Support Rule).
Item Count	The number of times the given rule and group appears in the database.
Maximum Confidence (max conf)	The maximum of conf(A=>B) and conf (B=>A).
Confidence of A=>B (conf(A=>B))	If A exists, what is likelihood of B. For example, if the appears in the database, what is the likelihood the group is the given group.
Confidence of B=>A (conf(B=>A))	If B exists, what is likelihood of A. For example, given the group, what is the likelihood of the rule.
Confidence of A=>~B (conf(A=>~B))	If A exists, what is the likelihood that the group will be any group other than B. For example, if the rule appears in the database, what is the likelihood that the group will be any group other than the group that was given.

CHAPTER V

MODIFIED METHODOLOGY AND RESULTS

5.1 EFA Results

Exploratory factor analysis (EFA) was conducted in SPSS to appraise the factor structure of the survey instrument items. More specifically, Principal Components factoring utilizing a Promax rotation was the extraction method for this analysis (Williams et al., 2010). Kaiser normalization (eigenvalue>1) was used to determine the number of extracted factors. As factor loading cut offs vary in the literature, this research used a conventional liberal-to-conservative continuum, with all factor loadings of 0.4 or higher being considered salient for this study, and cross-loadings greater than .2 were considered for elimination (Knekta et al., 2019; Matsunaga, 2010).

The initial iteration of the EFA was conducted on the eight self-efficacy (SE) items, eight adult hope (AH) items, six heath consciousness (HC) items, six health motivation (HM) items, twenty big 5 (Big 5) items, three Perceived Persuasiveness items, three Intention items, four Willingness to Use items, and the four marker variable (MV) questions (n=62). It was observed that all the SE constructs and AH constructs were cross loading, therefore AH was eliminated due to SE being regarded as a core premise of human performance across multiple domains and AH measurements conceptually and operationally functioning synonymously as SE (Zhou & Kam, 2016). Multicollinearity issues were identified between Perceived Persuasiveness, Intention, and Willingness to Use therefore, the Intention and Willingness to Use constructs were eliminated from the model due to Perceived Persuasiveness being studied across multiple domains and Perceived Persuasiveness being more pursuant to the current study. A total of 16 items (HM_1, HM_2, Big 5-Conscientiousness (R) Q8, Big 5-Conscientiousness (R) Q18, all 4 Big 5-Agreeableness items, all 4 Big 5-Openess items, and all 4 Big 5-Neuroticcism items were eliminated due to cross loading issues. An additional 2 items Big 5-Conscientiousness Q3 and Big 5-Conscientiousness Q13 were eliminated for having correlation coefficients below the threshold and failing to load properly on other items.

For the final stage, principal components factor analysis of the remaining 29 items resulting in six extracted six factors explaining 73.67% of the variance. The factor loading matrix for the final solution is presented in Table 10. Hypotheses 2, 5, 6, 8, and 9 are untestable because of the EFA results.

5.2 Aim 1 Results

Weighted scores were computed for self-efficacy, health consciousness, health motivation, extraversion, and perceived persuasiveness using the final EFA factor loadings. Table 11 presents the Cronbach's alphas, means, standard deviations and intercorrelation among the variables included in this study

To address Aim 1, a linear regression analysis was performed on the weighted variables. Two linear regression models were conducted. Table 12 displays the regression

Table 10. Final EFA Results

	Factor					
	1	2	3	4	5	6
SE Q1	0.736					
SE Q2	0.872					
SE Q3	0.902					
SE Q4	0.908					
SE Q5	0.914					
SE Q6	0.793					
SE Q7	0.686					
SE Q8	0.821					
HC Q1		0.817				
HC Q2		0.848				
HC Q3		0.782				
HC Q4		0.714				
HC Q5		0.653				
HC Q6		0.457				
HM Q3			0.781			
HM Q4			0.847			
HM Q5			0.878			
HM Q6			0.728			
TF_PP Q1				0.973		
TF_PP Q2				0.999		
TF_PP Q3				0.989		
MV 1					0.858	
MV 2					0.821	
MV 3					0.710	
MV 4					0.830	
E Q1						0.408
E Q6						0.624
E Q11						0.566
E Q16						0.768

Notes. SE values are Self-Efficacy. HC values are Health Consciousness. HM values are Health Motivation. TF_PP values are Perceived Persuasiveness. MV values are Marker Variables. E values are Extraversion.

Table 11. Correlation Matrix for Weighted Variables

Variable	*M*	*SD*	cα	1.	2.	3.	4.	5.	6.
1. Self-Efficacy	4.574	0.852	.939	.833					
2. Health Consciousness	3.455	0.994	.858	.239**	.724				
3. Health Motivation	3.071	1.205	.862	.067**	-.132**	.811			
4. Extraversion	2.110	0.816	.699	.263**	.142**	-.069**	.605		
5. Perceived Persuasiveness	3.822	2.047	.977	.283**	.529**	.081**	.159**	.987	
6. Marker Variable	3.089	1.135	.840	.153**	.391**	.303**	-.030*	.363**	.807

Notes. Values on the diagonal are the square root of the average variance extracted (AVE). *$p < .05$. **$p < .01$.

coefficients. Model 1 included the demographic control variables of gender, age, and education level as predictors of perceived persuasiveness. The demographic variables were dummy-coded with “male” serving as the reference category for gender, “under 40” serving as the reference category for age, and “less than high school” serving as the reference category for education level. The *F*-test (i.e., analysis of variance) for Model 1 was significant, $F_{(9, 6540)} = 191.806$, $p < .001$, with an adjusted R^2 of .208, indicating that the demographic variables explained 20.8% of the variance in perceived persuasiveness. Gender was a significant predictor, with females having higher perceived persuasiveness ($B = 0.127$, $SE = 0.048$, $t_{(6540)} = 2.668$, $p = .008$) and non-binary individuals having lower perceived persuasiveness ($B = -2.856$, $SE = 0.265$, $t_{(6540)} = -10.767$, $p < .001$) relative to males. Age was a significant predictor, with individuals in the 40-59 age group ($B = -0.643$, $SE = 0.069$, $t_{(6540)} = -9.377$, $p < .001$) and 60+ age group ($B = -2.116$, $SE = 0.059$, $t_{(6540)} = -35.752$, $p < .001$) having lower perceived persuasiveness relative to individuals aged 40 and under. Education level was a significant predictor, as individuals who held associate degrees ($B = -0.411$, $SE = 0.163$, $t_{(6540)} = -2.514$, $p = .012$) and bachelor’s degrees ($B = -0.581$, $SE = 0.157$, $t_{(6540)} = -3.696$, $p < .001$) tended to have lower perceived persuasiveness relative to individuals who had not completed high school.

In Model 2, the theorized effects were added as predictors. The *F*-test for Model 2 was significant, $F_{(13, 6536)} = 341.035$, $p < .001$, with an adjusted R^2 of .403, indicating that the demographic variables, self-efficacy, health consciousness, health motivation, and extraversion together explained 40.3% of the variance in perceived persuasiveness. Table 12 displays the regression coefficients for Model 2. The non-binary category of gender

Table 12. Results for Multiple Linear Regression Models

Variable	Model 1				Model 2			
	B	*SE*	*t*	Sig.	*B*	*SE*	*t*	Sig.
(Constant)	5.406***	0.161	33.531	< .001	0.005	0.202	0.023	.981
<u>Control Variables</u>								
Gender (Female)	0.127**	0.048	2.668	.008	-0.002	0.042	-0.048	.962
Gender (Non-binary)	-2.856***	0.265	-10.767	< .001	-2.239***	0.238	-9.412	< .001
Age (40-59)	-0.643***	0.069	-9.377	< .001	-0.477***	0.061	-7.869	< .001
Age (60+)	-2.116***	0.059	-35.752	< .001	-1.388***	0.054	-25.816	< .001
Education (High school graduate)	-0.302	0.161	-1.880	.060	-0.218	0.140	-1.555	.120
Education (Some college no degree)	-0.279	0.156	-1.782	.075	-0.462***	0.137	-3.378	< .001
Education (Associate degree)	-0.411*	0.163	-2.514	.012	-0.389**	0.142	-2.731	.006
Education (Bachelor degree)	-0.581***	0.157	-3.696	< .001	-0.624***	0.137	-4.542	< .001
Education (Graduate degree)	-0.059	0.159	-0.370	.711	-0.555	0.139	-3.985	< .001
<u>Theorized Effects</u>								
Self-Efficacy					0.263***	0.026	10.174	< .001
Health Consciousness					0.883***	0.022	40.000	< .001
Health Motivation					0.200***	0.017	11.597	< .001
Extraversion					0.150***	0.026	5.884	< .001

Notes. *N* = 6550. *Model 1* R^2=.208. *Model 2* R^2=.403.

remained a significant predictor, however, the female category of gender was no longer significant in Model 2 (B = -0.002, SE = 0.042, $t_{(6536)}$ = -0.048, p = .962). Both categories of age remained as significant predictors in Model 2. The associate and bachelor categories of education level remained as significant predictors in Model 2, and the categories of some college (B = -0.462, SE = 0.137, $t_{(6536)}$ = -3.378, $p < .001$) and graduate degree (B = -0.555, SE = 0.139, $t_{(6536)}$ = -3.985, $p < .001$) became significant in Model 2. Self-efficacy was a significant positive predictor (B = 0.263, SE = 0.026, $t_{(6536)}$ = 10.174, $p < .001$), indicating that individuals higher in self-efficacy tended to have higher perceived persuasiveness. Health consciousness was a significant positive predictor (B = 0.883, SE = 0.022, $t_{(6536)}$ = 40.000, $p < .001$), indicating that individuals higher in health consciousness tended to have higher perceived persuasiveness. Health motivation was a significant positive predictor (B = 0.200, SE = 0.017, $t_{(6536)}$ = 11.597, $p < .001$), indicating that individuals higher in health motivation tended to have higher perceived persuasiveness. Extraversion was a significant positive predictor (B = 0.150, SE = 0.026, $t_{(6536)}$ = 5.884, $p < .001$), indicating that individuals higher in extraversion tended to have higher perceived persuasiveness. The results of the hypothesis testing are presented in Table 13.

5.3 Aim 2 Results

To address Aim 2 contrast mining was used to discover significant personality characteristic differences that did not occur at random. For contrast pattern mining to occur, continuous data must be transferred to bins determined from the distribution of the

Table 13. Results of Tested Hypothesis

Hypothesis	Result
Hypothesis 1: Self-Efficacy will positively influence interpreted mHealth screen perceived persuasiveness.	Supported
Hypothesis 3: Health Consciousness will positively influence interpreted mHealth screen perceived persuasiveness.	Supported
Hypothesis 4: Health Motivation will positively influence interpreted mHealth screen perceived persuasiveness.	Supported
Hypothesis 7: Extraversion will positively influence interpreted mHealth screen perceived persuasiveness.	Supported

data. Contrast mining algorithms discretize continuous attributes into bins of approximately equal-sized intervals (Dong & Bailey, 2012). Table 14 shows the bins and labels of all continuous attributes. The first bin is labeled as 1, continuing to the third bin which is labeled as 3.

Table 15 shows the contrast mining rules with acceptable lift and association support values for Primary Category 1 (Primary Task Support). Table 15 can be interpreted as follows:

1. When the Perceived Persuasiveness Weighted value is within bin 3 (4.46, 6.91), the mHealth app screen's primary category tends to be Primary Task Support with an association support of 8.9%.

Table 16 gives the extended rule values for the contrast mining rules with acceptable lift and association support values for Primary Category 1 (Primary Task Support). Table 16 can be interpreted as follows:

Table 14. Bin and Labels for Attributes

Measurements	Bin	Label
Self-Efficacy Weighted	(0.83, 4.01)	1
	(4.03, 4.79)	2
	(4.8, 5.8)	3
Health Consciousness_Weighted	(0.71, 2.84)	1
	(2.86, 3.76)	2
	(3.78, 4.98)	3
Health Motivation_Weighted	(0.81, 2.61)	1
	(2.62, 3.68)	2
	(3.74, 5.66)	3
Extraversion_Weighted	(0.59, 1.82)	1
	(1.84, 2.58)	2
	(2.59, 4.14)	3
Perceived Persuasiveness_Weighted	(0.99, 2.97)	1
	(2.98, 4.61)	2
	(4.62, 6.91)	3

1. Perceived Persuasiveness Weighted within bin 3 (4.46, 6.91) appears in the Primary Task Support group 44.6% of the time. Of the remaining groups (dialogue support, system credibility support, and social support), the maximum percentage of time the Perceived Persuasiveness Weighted value within bin 3 (4.46, 6.91) is achieved by another single group is 43.1% of the time. Of the remaining groups (dialogue support, system credibility support, and social support), the minimum percentage of time the Perceived Persuasiveness Weighted value within bin 3 (4.46, 6.91) is achieved by another single group is 36.6% of the time. The maximum absolute difference between the maximum support of the opposing group and the support rule and the minimum support of the opposing group and the support rule is 8.0%. Perceived Persuasiveness Weighted within bin 3 (4.46, 6.91) appears in the

Primary Task Support group 584 times. If Perceived Persuasiveness Weighted within bin 3 (4.46, 6.91) appears in the database, the likelihood that the group is Primary Task Support is 21.7%. If the Primary Task Support group appears in the database, the likelihood that the Perceived Persuasiveness Weighted value will be within bin 3 (4.46, 6.91) is 44.6%. If Perceived Persuasiveness Weighted within bin 3 (4.46, 6.91) appears in the database, the likelihood that the group will be any other group besides Primary Task Support is 78.3%.

Table 17 shows the contrast mining rules with acceptable lift and association support values for Primary Category 2 (Dialogue Support). Table 17 can be interpreted as follows:

1. When the Self-Efficacy Weighted value is within bin 1 (0.083, 4.01), the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), and the Age is 60 or older, the mHealth app screen's primary category tends to be Dialogue Support with the association support of 1.8%.
2. When the Self-Efficacy Weighted value is within bin 2 (4.03, 4.79), the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), and the Gender is female, the mHealth app screen's primary category tends to be Dialogue Support with the association support of 1%.

Table 15. Contrast Mining Results with Acceptable Lift and Association Support Values for Primary Task Support

Rule	SE W	HC W	HM W	E W	PP W	Gender	Age	Education	A_G C	A_E C	Lift	Asc Supp	Max Conf
1	0	0	0	0	3	0	0	0	0	0	1.082	0.089	0.446

Notes. SE W values are Self-Efficacy Weighted. HC W values are Health Consciousness Weighted. HM values are Health Motivation Weighted. E W values are Extraversion Weighted. PP W values are Perceived Persuasiveness Weighted. A_G C values are Age and Gender Combined. A_E C values are Age and Education Combined.

Table 16. Extended Contrast Mining Results for Primary Task Support

Rule	Support Rule	Max Supp Opp Group	Min Supp Opp Group	Max Abs Diff in Con Supp	Item Count	Conf (A=>B)	Conf (B=>A)	Conf (A=>~B)
1	0.446	0.431	0.366	0.080	584	0.217	0.446	0.783

Notes. Max Supp Opp Group values are Maximum support of the opposing group. Min Supp Opp Group values are Minimum Support of Opposing Group. Max Abs Diff in Con Supp values are Maximum Absolute Difference in Contrast Support. Conf values are confidence.

3. When the Health Consciousness Weighted value is within bin 3 (3.78, 4.98), the Health Motivation Weighted value is within bin 1 (0.81, 2.61), the Extraversion Weighted value is within bin 1 (0.59, 1.892), and the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), the mHealth app screen's primary category tends to be Dialogue Support with the association support of 1.1%.
4. When the Self-Efficacy Weighted value is within bin 2 (4.03, 4.79), the Health Motivation Weighted value is within bin 1 (0.81, 2.61), and the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), the mHealth app screen's primary category tends to be Dialogue Support with the support of 1.1%.

Extended rule values are given in Table 18.

Table 19 shows the contrast mining rules with acceptable lift and association support values for Primary Category 3 (System Credibility). Table 19 can be interpreted as follows:

1. When the Self-Efficacy Weighted value is within bin 2 (4.03, 4.79), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the Gender is female, and the Age is 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.1%.
2. When the Self-Efficacy Weighted value is within bin 2 (4.03, 4.79), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Age/Gender combination is female 60 or older, the mHealth app screen's

Table 17. Contrast Mining Results with Acceptable Lift and Association Support Values for Dialogue Support

Rule	SE W	HC W	HM W	E W	PP W	Gender	Age	Education	A_G C	A_E C	Lift	Asc Supp	Max Conf
1	2	0	0	0	3	2	0	0	0	0	1.190	0.018	0.333
2	1	0	0	0	3	0	3	0	0	0	1.190	0.010	0.333
3	2	0	1	0	3	0	0	0	0	0	1.190	0.011	0.333
4	0	3	1	1	3	0	0	0	0	0	1.180	0.011	0.330

Notes. SE W values are Self-Efficacy Weighted. HC W values are Health Consciousness Weighted. HM values are Health Motivation Weighted. E W values are Extraversion Weighted. PP W values are Perceived Persuasiveness Weighted. A_G C values are Age and Gender Combined. A_E C values are Age and Education Combined.

Table 18. Extended Contrast Mining Results for Dialogue Support

Rule	Support Rule	Max Supp Opp Group	Min Supp Opp Group	Max Abs Diff in Con Supp	Item Count	Conf (A=>B)	Conf (B=>A)	Conf (A=>~B)
1	0.064	0.064	0.044	0.020	118	0.333	0.064	0.667
2	0.037	0.032	0.023	0.014	67	0.333	0.037	0.667
3	0.039	0.036	0.027	0.013	72	0.333	0.039	0.667
4	0.040	0.037	0.027	0.012	73	0.330	0.040	0.670

Notes. Max Supp Opp Group values are Maximum support of the opposing group. Min Supp Opp Group values are Minimum Support of Opposing Group. Max Abs Diff in Con Supp values are Maximum Absolute Difference in Contrast Support. Conf values are confidence.

primary category tends to be System Credibility Support with the association support of 1.1%.

3. When the Self-Efficacy Weighted value is within bin 2 (4.03, 4.79), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Gender is female, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.8%.
4. When the Self-Efficacy Weighted value is within bin 2 (4.03, 4.79), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Gender is female, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.0%.
5. When the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Age/Gender combination is female under 40, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.0%.
6. When the Extraversion Weighted value is within bin 1 (0.59, 1.82), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Gender is female, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.6%.
7. When the Extraversion Weighted value is within bin 1 (0.59, 1.82), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Age/Gender combination is female 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.2%.

8. When the Extraversion Weighted value is within bin 1 (0.59, 1.82), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the Gender is female, and the age is 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.2%.
9. When the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the Gender is female, and the Education is bachelor's degree in college (4-year), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.1%.
10. When the Health Consciousness value is within bin 2 (2.86, 3.76), the Health Motivation Weighted value is within bin 2 (2.62, 3.68), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Gender is female, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.1%.
11. When the Self-Efficacy Weighted value is within bin 2 (4.03, 4.79), the Health Consciousness Weighted value is within bin 2 (2.86, 3.76), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Gender is female, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.2%.
12. When the Extraversion Weighted value is within bin 3 (2.59, 4.14) and the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.6%.

13. When the Health Consciousness Weighted value is within bin 3 (3.78, 4.98), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Gender is female, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.1%.
14. When the Extraversion Weighted value is within bin 3 (2.59, 4.14), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the Gender is female, and the Age is 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.2%.
15. When the Self-Efficacy Weighted value is within bin 2 (4.03, 4.79), the Health Consciousness Weighted value is within bin 2 (2.86, 3.76), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Age is 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.1%.
16. When the Health Motivation Weighted value is within bin 2 (2.62, 3.68), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Gender is female, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.5%.
17. When the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61) and the Education is bachelor's degree in college (4-year), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.7%.

18. When the Extraversion Weighted value is within bin 1 (0.59, 1.82), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Age is 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.8%.
19. When the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Age is under 40, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.4%.
20. When the Health Consciousness Weighted value is within bin 2 (2.86, 3.76), the Extraversion Weighted value is within bin 1 (0.59, 1.82), and the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61) primary, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.3%.
21. When the Health Motivation Weighted value is within bin 1 (0.81, 2.61), the Extraversion Weighted value is within bin 1 (0.59, 1.82), and the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.2%.
22. When the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61) and the Gender is female, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 4.2%.
23. When the Health Consciousness Weighted value is within bin 3 (3.78, 3.76), the Health Motivation Weighted value is within bin 1 (0.81, 2.61), the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), the

Gender is female, and the Age is 60 and older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.2%.

24. When the Health Consciousness Weighted value is within bin 3 (3.78, 3.76), the Health Motivation Weighted value is within bin 1 (0.81, 2.61), the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), and the Age/Gender combination is female 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.2%.
25. When the Self-Efficacy Weighted value is within bin 2 (4.03, 4.79), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Age is 60 older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.7%.
26. When the Health Consciousness Weighted value is within bin 3 (3.78, 4.98), the Health Motivation Weighted value is within bin 1 (0.81, 2.61), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Age is 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.4%.
27. When the Health Motivation Weighted value is within bin 1 (0.81, 2.61), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Gender is female, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.5%.

28. When the Health Motivation Weighted value is within bin 3 (3.74, 5.66), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Gender is female, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.3%.
29. When the Health Consciousness Weighted value is within bin 2 (2.86, 3.76), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and Gender is female, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 2.5%.
30. When the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the Gender is female, and the Education is some college no degree, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.3%.
31. When the Health Motivation Weighted value is within bin 3 (3.74, 5.66), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the Gender is female, and the Age is 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.0%.
32. When the Health Motivation Weighted value is within bin 3 (3.74, 5.66), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Age/Gender combination is female 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.0%.

33. When the Self-Efficacy Weighted value is within bin 1 (0.83, 4.01), the Health Consciousness Weighted value is within bin 2 (2.86, 3.76), and the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.0%.
34. When the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the Gender is female, and the Age is 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 2.8%.
35. When the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Age/Gender combination is female 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 2.8%.
36. When the Health Consciousness Weighted value is within bin 3 (3.78, 4.98) and the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.8%.
37. When the Self-Efficacy Weighted value is within bin 2 (4.03, 4.79), the Health Consciousness Weighted value is within bin 2 (2.86, 3.76), and the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.7%.

38. When the Extraversion Weighted value is within bin 1 (0.59, 1.82) and the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 2.7%.
39. When the Health Consciousness Weighted value is within bin 2 (2.86, 3.76), the Health Motivation Weighted value is within bin 1 (0.81, 2.61), and the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.2%.
40. When the Health Consciousness Weighted value is within bin 3 (3.78, 4.98), the Extraversion Weighted value is within bin 3 (2.59, 4.14), the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), and the Age is 60 and older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.0%.
41. When the Self-Efficacy Weighted value is within bin 2 (4.03, 4.79) and the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 2.8%.
42. When the Health Consciousness Weighted value is within bin 3 (3.78, 4.98), the Health Motivation Weighted value is within bin 1 (0.81, 2.61), the Extraversion Weighted is within bin 3, and the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), the mHealth app screen's primary

category tends to be System Credibility Support with the association support of 1.5%.

43. When the Health Motivation Weighted value is within bin 3 (3.74, 5.66) and the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.7%.
44. When the Health Motivation Weighted value is within bin 3 (3.74, 5.66), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Age is 60 and older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.3%.
45. When the Health Consciousness Weighted value is within bin 2 (2.86, 3.76), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the Gender is female, and the Age is 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.6%.
46. When the Health Consciousness Weighted value is within bin 2 (2.86, 3.76), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Age/Gender combination is female 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.6%.
47. When the Health Motivation Weighted value is within bin 1 (0.81, 2.61), the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), the Gender is female, and the Age is 60 or older, the mHealth app screen's

primary category tends to be System Credibility Support with the association support of 1.8%.

48. When the Health Motivation Weighted value is within bin 1 (0.81, 2.61), the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), and the Age/Gender combination is female 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.8%.
49. When the Health Consciousness value is within bin 2 (2.86, 3.76), the Health Motivation Weighted value is within bin 2 (2.62, 3.68), and the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.3%.
50. When the Health Motivation Weighted value is within bin 1 (0.81, 2.61) and the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 2.7%.
51. When the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61) and the Education is some college no degree, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.7%.
52. When the Self-Efficacy Weighted value is within bin 1 (0.83, 4.01), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the

Gender is female, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.3%.

53. When the Health Consciousness value is within bin 2 (2.86, 3.76) and the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 3.4%.
54. When the Self-Efficacy Weighted value is within bin 3 (4.8, 5.8), the Health Consciousness value is within bin 3 (3.78, 4.98), the Health Motivation Weighted value is within bin 1 (0.81, 2.61), the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), and the Gender is female, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.1%.
55. When the Health Consciousness Weighted value is within bin 2 (2.86, 3.76), the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), and the Age is 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 2.0%.
56. When the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 6.6%.
57. When the Self-Efficacy Weighted value is within bin 3 (4.8, 5.8), the Health Consciousness value is within bin 3 (3.78, 4.98), the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), and the Age is 60 or older, the

mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.3%.

58. When the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61) and the Age is 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 3.8%.
59. When the Extraversion Weighted value is within bin 2 (1.84, 2.58), Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), and the Age is 60 or older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.5%.
60. When the Health Motivation Weighted value is within bin 1 (0.81, 2.61), the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), and the Age is 60 and older, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 2.1%.
61. When the Self-Efficacy Weighted value is within bin 3 (4.8, 5.8) and the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.9%.
62. When the Health Motivation Weighted value is within bin 1 (0.81, 2.61), the Extraversion Weighted value is within bin 2 (1.84, 2.58), and the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.4%.

63. When the Self-Efficacy Weighted value is within bin 1 (0.83, 4.01) and the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.8%.
64. When the Self-Efficacy Weighted value is within bin 3 (4.8, 5.8), the Health Motivation value is within bin 1 (0.81, 2.61), the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), and the Gender is female, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.5%.
65. When the Health Motivation Weighted value is within bin 2 (2.62, 3.68) and the Perceived Persuasiveness Weighted value is within bin 2 (2.98, 4.61), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 2.2%.
66. When the Self-Efficacy Weighted value is within bin 2 (4.03, 4.79), the Perceived Persuasiveness Weighted value is within bin 1 (0.99, 2.97), and Gender is male, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 2.1%.
67. When the Health Consciousness Weighted value is within bin 3 (3.78, 4.98), the Extraversion Weighted value is within bin 3 (2.59, 4.14), and the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 2.3%.

68. When the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), the Gender is female, and the Education is graduate's degree, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.2%.
69. When the Health Consciousness Weighted value is within bin 3 (3.78, 4.98), the Health Motivation Weighted value is within bin 1 (0.81, 2.61), the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), and the Gender is male, the mHealth app screen's primary category tends to be System Credibility Support with the association support of 1.9%.
70. When the Self-Efficacy Weighted value is within bin 3 (4.8, 5.8), the Health Consciousness value is within bin 3 (3.78, 4.98), the Health Motivation Weighted value is within bin 1 (0.81, 2.61), and the Perceived Persuasiveness Weighted value is within bin 3 (4.62, 6.91), the mHealth app screen's primary category tends to be System Credibility Support with the association support of 2.3%.

Extended rule values are given in Table 20.

Table 21 shows the contrast mining rules with acceptable lift and association support values for Primary Category 4 (Social Support). Table 21 can be interpreted as follows:

1. When the Perceived Persuasiveness Weighted value is within bin 1 (0.99, 2.97), the mHealth app screen's primary category tends to be Social Support with the association support of 9.4%.

2. When the Perceived Persuasiveness Weighted value is within bin 1 (0.99, 2.97), and the Age is 60 or older, the mHealth app screen's primary category tends to be Social Support with the association support of 7.0%.

Extended rule values are given in Table 20.

Table 19. Contrast Mining Results with Acceptable Lift and Association Support Values for System Credibility

Rule	SE W	HC W	HM W	E W	PP W	Gender	Age	Education	A_G C	A_E C	Lift	Asc Supp	Max Conf
1	2	0	0	0	2	2	3	0	0	0	1.339	0.011	0.429
2	2	0	0	0	2	0	0	0	6	0	1.339	0.011	0.429
3	2	0	0	0	2	2	0	0	0	0	1.318	0.018	0.422
4	0	0	0	0	2	2	1	0	0	0	1.317	0.010	0.421
5	0	0	0	0	2	0	0	0	4	0	1.317	0.010	0.421
6	0	0	0	1	2	2	0	0	0	0	1.257	0.016	0.402
7	0	0	0	1	2	0	0	0	6	0	1.256	0.012	0.402
8	0	0	0	1	2	2	3	0	0	0	1.256	0.012	0.402
9	0	0	0	0	2	2	0	5	0	0	1.246	0.011	0.399
10	0	2	2	0	2	2	0	0	0	0	1.236	0.011	0.395
11	2	2	0	0	2	2	0	0	0	0	1.234	0.012	0.395
12	0	0	0	3	2	0	0	0	0	0	1.231	0.016	0.394
13	0	3	0	0	2	2	0	0	0	0	1.230	0.011	0.393
14	0	0	0	3	2	2	0	0	0	0	1.218	0.012	0.390
15	2	2	0	0	2	0	0	0	0	0	1.211	0.011	0.388
16	0	0	2	0	2	2	0	0	0	0	1.210	0.015	0.387
17	0	0	0	0	2	0	0	5	0	0	1.204	0.017	0.385
18	0	0	0	1	2	0	3	0	0	0	1.193	0.018	0.382
19	0	0	0	0	2	0	1	0	0	0	1.193	0.014	0.382
20	0	2	0	1	2	0	0	0	0	0	1.191	0.013	0.381
21	0	0	1	1	2	0	0	0	0	0	1.187	0.012	0.380
22	0	0	0	0	2	2	0	0	0	0	1.184	0.042	0.379
23	0	3	1	0	3	2	3	0	0	0	1.182	0.012	0.378
24	0	3	1	0	3	0	0	0	6	0	1.182	0.012	0.378

Table 19 Cont.

25	2	0	0	0	2	0	3	0	0	0	1.174	0.017	0.376
26	0	3	1	0	2	0	3	0	0	0	1.172	0.014	0.375
27	0	0	1	0	2	2	0	0	0	0	1.170	0.015	0.375
28	0	0	3	0	2	2	0	0	0	0	1.170	0.013	0.374
29	0	2	0	0	2	2	0	0	0	0	1.169	0.025	0.374
30	0	0	0	0	2	2	0	3	0	0	1.167	0.013	0.373
31	0	0	3	0	2	2	3	0	0	0	1.165	0.010	0.373
32	0	0	3	0	2	0	0	0	6	0	1.165	0.010	0.373
33	1	2	0	0	2	0	0	0	0	0	1.163	0.010	0.372
34	0	0	0	0	2	2	3	0	0	0	1.162	0.028	0.372
35	0	0	0	0	2	0	0	0	6	0	1.162	0.028	0.372
36	0	3	0	0	2	0	0	0	0	0	1.156	0.018	0.370
37	2	2	0	0	2	0	0	0	0	0	1.155	0.017	0.369
38	0	0	0	1	2	0	0	0	0	0	1.152	0.027	0.369
39	0	2	1	0	2	0	0	0	0	0	1.148	0.012	0.367
40	0	3	0	3	3	0	3	0	0	0	1.146	0.010	0.367
41	2	0	0	0	2	0	0	0	0	0	1.144	0.028	0.366
42	0	3	1	3	3	0	0	0	0	0	1.143	0.015	0.366
43	0	0	3	0	2	0	0	0	0	0	1.142	0.017	0.365
44	0	0	3	0	2	0	3	0	0	0	1.139	0.013	0.364
45	0	2	0	0	2	2	3	0	0	0	1.136	0.016	0.364
46	0	2	0	0	2	0	0	0	6	0	1.136	0.016	0.364
47	0	0	1	0	3	2	3	0	0	0	1.130	0.018	0.362
48	0	0	1	0	3	0	0	0	6	0	1.130	0.018	0.362
49	0	2	2	0	2	0	0	0	0	0	1.127	0.013	0.361
50	0	0	1	0	2	0	0	0	0	0	1.123	0.027	0.360

Table 19 Cont.

51	0	0	0	0	2	0	0	3	0	0	1.121	0.017	0.359
52	1	0	0	0	2	2	0	0	0	0	1.116	0.013	0.357
53	0	2	0	0	2	0	0	0	0	0	1.115	0.034	0.357
54	3	3	1	0	3	2	0	0	0	0	1.114	0.011	0.356
55	0	2	0	0	2	0	3	0	0	0	1.112	0.020	0.356
56	0	0	0	0	2	0	0	0	0	0	1.111	0.066	0.355
57	3	3	0	0	3	0	3	0	0	0	1.109	0.013	0.355
58	0	0	0	0	2	0	3	0	0	0	1.106	0.038	0.354
59	0	0	0	2	3	0	3	0	0	0	1.096	0.015	0.351
60	0	0	1	0	3	0	3	0	0	0	1.094	0.021	0.350
61	3	0	0	0	2	0	0	0	0	0	1.089	0.019	0.348
62	0	0	1	2	3	0	0	0	0	0	1.086	0.014	0.347
63	1	0	0	0	2	0	0	0	0	0	1.083	0.018	0.347
64	3	0	1	0	3	2	0	0	0	0	1.074	0.015	0.344
65	0	0	2	0	2	0	0	0	0	0	1.074	0.022	0.344
66	2	0	0	0	1	1	0	0	0	0	1.071	0.021	0.343
67	0	3	0	3	3	0	0	0	0	0	1.070	0.023	0.343
68	0	0	0	0	3	2	0	6	0	0	1.070	0.012	0.342
69	0	3	1	0	3	2	0	0	0	0	1.062	0.019	0.340
70	3	3	1	0	3	0	0	0	0	0	1.060	0.023	0.339

Notes. SE W values are Self-Efficacy Weighted. HC W values are Health Consciousness Weighted. HM values are Health Motivation Weighted. E W values are Extraversion Weighted. PP W values are Perceived Persuasiveness Weighted. A_G C values are Age and Gender Combined. A_E C values are Age and Education Combined.

Table 20. Extended Contrast Mining Results for System Credibility

Rule	Support Rule	Max Supp Opp Group	Min Supp Opp Group	Max Abs Diff in Con Supp	Item Count	Conf (A=>B)	Conf (B=>A)	Conf (A=>~B)
1	0.036	0.025	0.021	0.015	75	0.429	0.036	0.571
2	0.036	0.025	0.021	0.015	75	0.429	0.036	0.571
3	0.058	0.039	0.035	0.023	121	0.422	0.058	0.578
4	0.032	0.023	0.018	0.014	67	0.421	0.032	0.579
5	0.032	0.023	0.018	0.014	67	0.421	0.032	0.579
6	0.051	0.040	0.031	0.021	107	0.402	0.051	0.598
7	0.038	0.029	0.024	0.014	80	0.402	0.038	0.598
8	0.038	0.029	0.024	0.014	80	0.402	0.038	0.598
9	0.033	0.027	0.018	0.015	69	0.399	0.033	0.601
10	0.033	0.027	0.021	0.013	70	0.395	0.033	0.605
11	0.037	0.029	0.024	0.013	77	0.395	0.037	0.605
12	0.050	0.040	0.031	0.019	104	0.394	0.050	0.606
13	0.034	0.027	0.021	0.013	72	0.393	0.034	0.607
14	0.036	0.028	0.024	0.012	76	0.390	0.036	0.610
15	0.033	0.027	0.021	0.012	69	0.388	0.033	0.612
16	0.046	0.037	0.031	0.015	96	0.387	0.046	0.613
17	0.053	0.045	0.031	0.022	111	0.385	0.053	0.615
18	0.056	0.045	0.040	0.016	118	0.382	0.056	0.618
19	0.044	0.038	0.025	0.019	92	0.382	0.044	0.618
20	0.041	0.037	0.028	0.012	85	0.381	0.041	0.619
21	0.038	0.033	0.027	0.011	79	0.380	0.038	0.620
22	0.133	0.106	0.094	0.039	278	0.379	0.133	0.621
23	0.036	0.033	0.018	0.018	76	0.378	0.036	0.622
24	0.036	0.033	0.018	0.018	76	0.378	0.036	0.622

Table 20. Cont.

25	0.053	0.044	0.040	0.014	112	0.376	0.053	0.624
26	0.043	0.039	0.023	0.020	90	0.375	0.043	0.625
27	0.048	0.041	0.035	0.012	100	0.375	0.048	0.625
28	0.039	0.036	0.027	0.012	82	0.374	0.039	0.626
29	0.077	0.068	0.056	0.022	162	0.374	0.077	0.626
30	0.042	0.035	0.028	0.013	87	0.373	0.042	0.627
31	0.031	0.031	0.021	0.011	66	0.373	0.031	0.627
32	0.031	0.031	0.021	0.011	66	0.373	0.031	0.627
33	0.032	0.034	0.020	0.012	67	0.372	0.032	0.628
34	0.088	0.073	0.066	0.022	184	0.372	0.088	0.628
35	0.088	0.073	0.066	0.022	184	0.372	0.088	0.628
36	0.055	0.047	0.040	0.015	115	0.370	0.055	0.630
37	0.052	0.047	0.037	0.015	109	0.369	0.052	0.631
38	0.085	0.074	0.061	0.024	178	0.369	0.085	0.631
39	0.038	0.037	0.027	0.010	79	0.367	0.038	0.633
40	0.031	0.028	0.021	0.010	66	0.367	0.031	0.633
41	0.089	0.074	0.070	0.019	186	0.366	0.089	0.634
42	0.047	0.040	0.035	0.012	98	0.366	0.047	0.634
43	0.052	0.048	0.039	0.014	110	0.365	0.052	0.635
44	0.039	0.037	0.028	0.011	82	0.364	0.039	0.636
45	0.052	0.046	0.041	0.011	108	0.364	0.052	0.636
46	0.052	0.046	0.041	0.011	108	0.364	0.052	0.636
47	0.055	0.054	0.031	0.024	115	0.362	0.055	0.638
48	0.055	0.054	0.031	0.024	115	0.362	0.055	0.638
49	0.040	0.037	0.029	0.011	84	0.361	0.040	0.639
50	0.083	0.073	0.067	0.016	174	0.360	0.083	0.640

Table 20. Cont.

51	0.054	0.049	0.040	0.014	113	0.359	0.054	0.641
52	0.041	0.041	0.024	0.017	85	0.357	0.041	0.643
53	0.106	0.100	0.082	0.024	223	0.357	0.106	0.643
54	0.034	0.035	0.021	0.013	72	0.356	0.034	0.644
55	0.063	0.059	0.051	0.012	132	0.356	0.063	0.644
56	0.205	0.180	0.165	0.040	430	0.355	0.205	0.645
57	0.039	0.038	0.027	0.012	82	0.355	0.039	0.645
58	0.120	0.106	0.098	0.022	252	0.354	0.120	0.646
59	0.048	0.047	0.030	0.018	101	0.351	0.048	0.649
60	0.066	0.068	0.038	0.028	139	0.350	0.066	0.650
61	0.059	0.055	0.044	0.014	123	0.348	0.059	0.652
62	0.043	0.047	0.024	0.019	90	0.347	0.043	0.653
63	0.058	0.062	0.040	0.017	121	0.347	0.058	0.653
64	0.048	0.050	0.032	0.016	100	0.344	0.048	0.656
65	0.070	0.066	0.055	0.015	146	0.344	0.070	0.656
66	0.065	0.062	0.053	0.012	136	0.343	0.065	0.657
67	0.071	0.067	0.060	0.011	149	0.343	0.071	0.657
68	0.036	0.039	0.025	0.011	76	0.342	0.036	0.658
69	0.059	0.060	0.038	0.021	123	0.340	0.059	0.660
70	0.073	0.076	0.054	0.019	153	0.339	0.073	0.661

Notes. Max Supp Opp Group values are Maximum support of the opposing group. Min Supp Opp Group values are Minimum Support of Opposing Group. Max Abs Diff in Con Supp values are Maximum Absolute Difference in Contrast Support. Conf values are confidence.

Table 21. Contrast Mining Results with Acceptable Lift and Association Support Values for Social Support

Rule	SE W	HC W	HM W	E W	PP W	Gender	Age	Education	A_G C	A_E C	Lift	Asc Supp	Max Conf
1	0	0	0	0	1	0	0	0	0	0	1.163	0.094	0.469
2	0	0	0	0	1	0	3	0	0	0	1.143	0.070	0.352

Notes. SE W values are Self-Efficacy Weighted. HC W values are Health Consciousness Weighted. HM values are Health Motivation Weighted. E W values are Extraversion Weighted. PP W values are Perceived Persuasiveness Weighted. A_G C values are Age and Gender Combined. A_E C values are Age and Education Combined.

Table 22. Extended Contrast Mining Results for Social Support

Rule	Support Rule	Max Supp Opp Group	Min Supp Opp Group	Max Abs Diff In Con Supp	Item Count	Conf (A=>B)	Conf (B=>A)	Conf (A=>~B)
1	0.469	0.392	0.376	0.094	615	0.233	0.469	0.767
2	0.352	0.298	0.296	0.056	461	0.229	0.352	0.771

Notes. Max Supp Opp Group values are Maximum support of the opposing group. Min Supp Opp Group values are Minimum Support of Opposing Group. Max Abs Diff in Con Supp values are Maximum Absolute Difference in Contrast Support. Conf values are confidence.

CHAPTER VI

DISCUSSION

This chapter describes the results of a data-driven examination of the patterns created when psychological traits and demographic variables are considered. This chapter also discusses the contributions this research makes to theory and practice. Limitations and recommendations for future research are given as well as the conclusion.

The purpose of this study was to examine whether psychological characteristics (self-efficacy, health consciousness, health motivation, and Big 5 personality traits) could enhance the perceived persuasiveness of digital health technologies. This study was designed to evaluate how these psychological characteristics impact the perceived persuasiveness of digital health technologies utilizing the PSD framework. Additionally, the dynamic intertwining of psychological characteristics that drive the perceived persuasiveness of the primary PSD technique categories were illuminated. Furthermore, this study opens the pathway for designers of digital health technologies to gain further knowledge of why individual characteristics must be considered during the design process. Keizer et al. (2020) suggested that the misalignment between end-users and digital technologies is often a result of developers failing to consider the end-user during the development process. While the benefits of the personalization of persuasive systems has been acknowledged, the field is still in its infancy, and there exits very little knowledge on the best way to tailor these technologies (Orji et al., 2018; Oyibo et al., 2019). The research findings suggest that using a dynamic, data-centered approach that considers the end-users' self-efficacy, health consciousness, health motivation, extraversion, age, gender, and education could be a way to increase the perceived persuasiveness of digital health technologies. Stakeholders are also offered a data science method that enhances the body of knowledge on tailoring of persuasive technologies.

6.1 Contributions To Theory

The study makes several contributions to the literature. First, this work produces new quantitative knowledge about the influence psychological characteristics (self-efficacy, health consciousness, health motivation, and extraversion) have on the perceived persuasiveness of digital health technologies. This work will help future researchers better engage users of digital health tools by using a dynamic, user-centered approach when implementing PSD principles. Second, the developed model helps to fill the gap, as one-size-fits-all solutions fail to consider how a user's perceived persuasiveness is impacted by their psychological characteristics.

To the best of our knowledge, this research is the first to use a combination of self-efficacy, health consciousness, health motivation, extraversion, gender, age, and education, to examine their impact on the effective engagement of the users of digital health technologies. By integrating psychological characteristics, this work advances the current state of understanding how psychological characteristics affect the perceived persuasiveness of persuasive technologies.

Finally, this work proposed the novel use of contrast mining to address the gap created by PSD frameworks not systematically incorporating data driven decisions. While the model developed in this research showed psychological characteristics and demographics to be significant predictors of perceived persuasiveness, contrast mining provided a multi-layer view of the impact these had on perceived persuasiveness at the screen level. The Primary Task Support category scored in the highest perceived persuasiveness weighted bin. This finding is contradicts Drozd et al. (2012) who did not find a significant relationship between primary task support and perceived persuasiveness. Screens from the System Credibility category had middle-level perceived persuasiveness weighted scores. The findings that primary task support and system credibility increase perceived persuasiveness are supported by Lehto (2012) who found that primary task support and system credibility both significantly impact perceived persuasiveness directly. Screens from the Social Support category in the scored in the lowest perceived persuasiveness bin.

This high-level category view provides a surface layer view that does not provide insight into tailoring digital health technologies for a diverse user base. However, contrast mining provides additional rules that allow the reader to see how the various combinations of characteristics and demographic values shifted the perceived persuasiveness of the digital health technology screens. It is through this lens that implications for practitioners are presented.

6.2 Implications For Practice

Besides the theoretical contributions to the field of persuasive technology, this research offers developers vital information pertaining to the user-centric development of persuasive digital health technologies. The information that has been gained can be used by designers to increase the perceived persuasiveness of digital health technologies by providing guidance on how to dynamically utilize PSD principles based on the individual's psychological characteristics and demographic makeup.

The use of contrast mining is not hypothesis driven and is particularly useful for discovering strong correlations between predictors that can lead toward future research. This method yielded a manageable set of rules that predicted when mHealth screen's primary categories of primary task support, dialogue support, system credibility support, or social support would be persuasive. The primary task support scores were above the average perceived persuasiveness score, followed by screens from the system credibility category which were close to or above the average score. Based on the findings, practitioners seeking to develop persuasive digital health technologies should develop screens using techniques in the primary task support or system credibility categories. Screens that employ techniques from the social support category should be avoided as they have low perceived persuasiveness scores. The contrast mining findings also suggest practitioners should use techniques from the dialogue support category when developing digital health technologies. All the rules from the dialogue support category with acceptable lift and association support values scored in the high perceived persuasiveness weighted bin.

Based on the major findings, the role of self-efficacy should be considered by persuasive technology designers. The statistical analysis found self-efficacy to be a significant positive predictor of perceived persuasiveness. Except for one rule, all the contrast mining persuasive technology category results that included self-efficacy had middle to high weighted perceived persuasiveness scores. Contrast mining analysis found males with middle-level self-efficacy weighted score had a 34.3% likelihood to find the perceived persuasiveness of screens in the system credibility support category to be low. Participants aged 60 and over with low self-efficacy found screens from the dialogue support category to be highly persuasive. There were no acceptable contrast mining rules containing self-efficacy values for screens from the primary task support and social support categories. Based on the perceived persuasiveness scores being at or above the mean, practitioners seeking to leverage self-efficacy, should create screens using techniques from the dialogue support and system credibility categories. Developers should be cautious about using screens from the system credibility support category with males with medium self-efficacy as it may lower the perceived persuasiveness of the digital health tool.

Multiple linear regression analyses found health consciousness to be a significant positive predictor of perceived persuasiveness. Participants with high-level health consciousness scores but low-level health motivation and extraversion scores had a 33% likelihood of scoring screens from the dialogue support category as highly persuasive. Practitioners should note that regardless of other psychological factors being low, having high health consciousness will drive high perceived persuasives on mHealth screens using dialogue support techniques. Participants with mid-level health consciousness weighted scores similarly scored the perceived persuasiveness of screens from the system credibility category in the middle bin. This scoring also held with females with the same health consciousness weighted score. Based on the findings, practitioners using health consciousness with their digital health technologies should utilize techniques from the system credibility category with individuals with mid-level health consciousness scores. Practitioners should also consider leveraging gender information, as they will need to present screens using system credibility techniques to females with mid-level health consciousness scores. No rules were given to provide insight on the impact of low health consciousness.

While the model found health motivation to be a significant positive predictor of perceived persuasiveness, contrast mining found that screens in the System Credibility category received high perceived persuasiveness values in spite of the participants low health motivation score. The findings show that individuals with low weighted health motivation scores from the lowest bin still scored screens in the System Credibility category in the highest perceived persuasiveness bin. This was especially seen in all females and females that were 60 and older. This finding suggests that techniques that enhance the credibility of digital health technologies are perceived as persuasive regardless of whether the user is motivated to be healthy.

Multiple linear regression analysis also found extraversion to be a significant positive predictor of perceived persuasiveness. Individuals with low weighted extraversion scores scored screens in the System Credibility category in the middle weighted perceived persuasiveness bin. Further analysis finds that this pattern holds with female participants. Individuals with high weighted extraversion scores scored screens in the system credibility category in the middle to high perceived persuasiveness bins.

Individuals with a combination high extraversion and health consciousness scored screens in the system credibility category as highly persuasive. The use of system credibility techniques is recommended for users with low and high extraversion scores.

Demographic data such as age and gender should also be considered by developers of digital health technologies. The findings strongly suggest the distribution of perceived persuasiveness shifts from negatively skewed to positively skewed as participants get older. Additionally, this shift occurs earlier in females (i.e., in the 40-59 age group) compared to males who do not shift until the oldest age group (i.e., in the 60 and older age group). Participants in the 60 and older age group indicated screens from the Social Support have low weighted perceived persuasiveness values. Females in the same age group scored screens in the System Credibility category as more persuasive.

Digital health technologies are one of the latest innovations in the healthcare industry. The ubiquitous nature of mobile devices makes them a key component in the treatment of consumers/patients. To increase the perceived persuasiveness of digital health technologies, developers using the PSD model developed by Oinas-Kukkonen and Harjumaa (2009) should employ persuasive technology design techniques which consider the psychological characteristics and demographics of the end-user. These considerations effect the perceived persuasiveness of these tools. Primary task support techniques are strongly associated with above average perceived persuasiveness and should be used to create persuasive digital health tools. Developers should sparingly utilize social support techniques as their weighted perceived persuasiveness is extremely low.

6.3 Limitations And Directions For Future Research

Despite the theoretical and practical contributions obtained in this study, there exist limitations that limit the generalizability of the findings. Further examination of the 40 and under age group indicates that only 7.3% of the participants were between the age of 18 and 29. Additional research should be completed that focuses on the younger population, ages 18 – 29.

Further study should cover the shift in perceived persuasiveness that was noted by gender and age. While gender was not significant when theorized effects were added to Model 2, contrast mining explicated some patterns that may guide researchers in developing studies that will determine the age group and PSD design categories that are causing this shift. This research found that participants 60 years or older did not perceive screens from the Social Support category to be persuasive but found screens for the System Credibility category to be more persuasive. These nuances could help explain the shift we are seeing across age groups. Furthermore, this study developed screens based on each of the twenty-eight PSD techniques. Further study should take a deeper dive into each of techniques in the four main categories.

The discretization process completed by the Contrast program produced bins that were not continuous. The gaps in the bin numbering could prove problematic for practitioners when digital health technology users have weighted psychological characteristic scores that do not fall in the generated range. Finally, the research only examines extraversion due to multicollinearity issues with other items from the Big-5 personality traits. Sleep et al. (2021) found longer measures to contain a considerably more variance than shorter, more condensed measures. Further study should use a more extensive Big Five personality test such as the Neo Personality Inventory (McCrae et al., 2005) rather than the Mini IPIP scale (Donnellan et al., 2006).

Little is known about how psychological characteristics and the combination of persuasive techniques from multiple categories affects perceived persuasiveness. Drozd et al. (2012) found that Primary Task Support and Dialogue Support together significantly impacted perceived persuasiveness. Additional studies that examine the primary and secondary categories are needed to determine whether or not the combination of additional categories is driving the perceived persuasiveness.

Previous evidence has shown that perceived persuasiveness can lead to higher engagement. Screens utilizing techniques from the primary task support and system credibility support categories have high perceived persuasiveness scores and should be used when making persuasive technologies. Conversely, screens integrating techniques from the social support category had very low perceived persuasive scores and should be omitted from applications using persuasive techniques. This research has identified key principles that practitioners should utilize and avoid, but further study needs to be done to evaluate a comparison against the categories that do not increase perceived persuasiveness. One key limitation of this study is the use of static screens. Developing a fully developed app will allow researchers to evaluate the engagement of the digital health tool. Running these studies in tandem will allow researchers to evaluate engagement on both of those to see if higher perceived persuasiveness leads to higher engagement.

6.4 Conclusion

The purpose of this study was to examine how the user's psychological characteristics influence the perceived persuasiveness of digital health technologies. This research contributes to advancing the fields of data-driven, user-centric development of persuasive technologies by investigating the intertwining of the user's psychological characteristics and the perceived persuasiveness of digital health technologies. This work opened a new research avenue by examining the roles psychological characteristics play in interpreting the perceived persuasiveness of mHealth screens. The use of dynamic data-driven capabilities is important to advancing perceived persuasiveness which has the potential to successfully engage users of digital health technologies. Evidence was presented to support the use of primary task support and system credibility support techniques being used in the development of persuasive technologies. Perceived persuasiveness scores were above average for mHealth screens utilizing techniques from the primary task support category and close to or above average for screens from the system credibility category Developers and practitioners should be careful utilizing only social support techniques as they were found to have very low perceived persuasive scores which indicates a lower ability to persuade mHealth app users to utilize the tool. This work also describes the roles psychological characteristics play in interpreted mHealth screen perceived persuasiveness. Evidence was provided that self-efficacy, health consciousness, health motivation, extraversion, gender, age, and education have a significant influence on the perceived persuasiveness of digital health technologies. Moreover, this research showed varying combinations of the psychological characteristics and demographic variables impacted the perceived persuasiveness of the primary persuasive technology category. Dynamic data-driven capabilities will allow designers of digital health technologies to overcome the gap stemming from one-size-fits-all approaches.

To our knowledge, this is the first study to leverage all twenty-eight individual persuasive design techniques using a traditional statistical approach and contrast pattern mining. While this research examined the individual screens at the category level, more extensive statistical analysis is needed to ascertain more interesting findings while contrast mining analysis can help detect more data-driven design opportunities.

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APPENDICES

Appendix A: IRB Form

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UNIVERSITY OF SOUTH ALABAMA

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INSTITUTIONAL REVIEW BOARD
January 30, 2020

Principal Investigator:	Scott Sittig		
IRB # and Title:	IRB PROTOCOL: 20-019 [1550884-1] Consumer Engagement Mobile Health Screen Design Using Persuasive Technology		
Status:	APPROVED	Review Type:	Exempt Review
Approval Date:	January 30, 2020	Submission Type:	New Project
Initial Approval:	January 30, 2020	Expiration Date:	
Review Category:	45 CFR 46.104 (d)(2): Research that only includes interaction involving the use of educational tests (cognitive, diagnostic, aptitude, achievement), survey procedures, interview procedures or observation of public behavior (including visual or auditory recording): ii. Any disclosure of the human subjects' responses outside of the research would not reasonably place the subjects at risk of criminal or civil liability or be damaging to the subjects' financial standing, employability, educational advancement, or reputation		

This panel, operating under the authority of the DHHS Office for Human Research and Protection, assurance number FWA 00001602, and IRB Database #00000286, has reviewed the submitted materials for the following:

1. *Protection of the rights and the welfare of human subjects involved.*
2. *The methods used to secure and the appropriateness of informed consent.*
3. *The risk and potential benefits to the subject.*

The regulations require that the investigator not initiate any changes in the research without prior IRB approval, except where necessary to eliminate immediate hazards to the human subjects, and that **all problems involving risks and adverse events be reported to the IRB immediately!**

Subsequent supporting documents that have been approved will be stamped with an IRB approval and expiration date (if applicable) on every page. Copies of the supporting documents must be utilized with the current IRB approval stamp unless consent has been waived.

Notes:

Appendix B: New General Self-Efficacy Scale

Derived from the New General Self-Efficacy Scale

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I will be able to achieve most of the goals that I have set for myself.	o	o	o	o	o	o	o
When facing difficult tasks, I am certain that I will accomplish them.	o	o	o	o	o	o	o
In general, I think that I can obtain outcomes that are important to me.	o	o	o	o	o	o	o
I believe I can succeed at most any endeavor to which I set my mind.	o	o	o	o	o	o	o
I will be able to successfully	o	o	o	o	o	o	o

overcome many challenges.							
I am confident that I can perform effectively on many different tasks.	o	o	o	o	o	o	o
Compared to other people, I can do most tasks very well.	o	o	o	o	o	o	o
Even when things are tough, I can perform quite well.	o	o	o	o	o	o	o

Appendix C: Adult Hope Scale

Derived from the Adult Hope Scale (AHS)

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I can think of many ways to get out of a jam.	o	o	o	o	o	o	o
I energetically pursue my goals.	o	o	o	o	o	o	o
There are lots of ways around any problem.	o	o	o	o	o	o	o
I can think of many ways to get the things in life that are important to me.	o	o	o	o	o	o	o
Even when others get discouraged, I know I can find a way to solve a problem.	o	o	o	o	o	o	o
My past experiences have prepared me well for the future.	o	o	o	o	o	o	o

I've been pretty successful in life.	o	o	o	o	o	o	o
I meet the goals that I set for myself.	o	o	o	o	o	o	o

Appendix D: Health Consciousness Scale

Derived from the Health Consciousness Scale

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I worry about the harmful chemicals in my food.	o	o	o	o	o	o	o
I am concerned about my drinking water quality.	o	o	o	o	o	o	o
I usually read the ingredients on food labels.	o	o	o	o	o	o	o
I read more health related articles than I did 3 years ago.	o	o	o	o	o	o	o
I am interested in information about my health.	o	o	o	o	o	o	o
I am concerned about my health all the time.	o	o	o	o	o	o	o

Appendix E: Health Motivation Scale

Derived from the Health Motivation Scale

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I try to prevent common health problems before I feel any symptoms.	o	o	o	o	o	o	o
I am concerned about common health risks and try to take action to prevent them.	o	o	o	o	o	o	o
I don't worry about common health risks until they become a problem for me or someone close to me.	o	o	o	o	o	o	o
Because there are so many illnesses that can hurt me these days, I am not going	o	o	o	o	o	o	o

to worry about them.							
I don't take any action against common health risks I hear about until I know I have a problem.	o	o	o	o	o	o	o
I would rather enjoy life than try to make sure I am not exposing myself to health risks.	o	o	o	o	o	o	o

Appendix F: Big 5 Mini-IPIP Scale

Derived from the Big 5 Mini-IPIP Scale

	Extremely Inaccurate	Moderately Inaccurate	Slightly Inaccurate	Neither Accurate nor Inaccurate	Slightly Accurate	Moderately Accurate	Extremely Accurate
Am the life of the party.	o	o	o	o	o	o	o
Sympathize with others' feelings.	o	o	o	o	o	o	o
Get chores done right away.	o	o	o	o	o	o	o
Have frequent mood swings.	o	o	o	o	o	o	o
Have a vivid imagination.	o	o	o	o	o	o	o
Don’t talk a lot.	o	o	o	o	o	o	o
Am not interested in other people’s problems.	o	o	o	o	o	o	o
Often forget to put things back in their proper place.	o	o	o	o	o	o	o
Am relaxed most of the time.	o	o	o	o	o	o	o
Am not interested in	o	o	o	o	o	o	o

abstract ideas.							
Talk to a lot of different people at parties.	o	o	o	o	o	o	o
Feel others' emotions.	o	o	o	o	o	o	o
Like order.	o	o	o	o	o	o	o
Get upset easily.	o	o	o	o	o	o	o
Have difficulty understandi ng abstract ideas.	o	o	o	o	o	o	o
Keep in the background.	o	o	o	o	o	o	o
Am not really interested in others.	o	o	o	o	o	o	o
Make a mess of things.	o	o	o	o	o	o	o
Seldom feel blue.	o	o	o	o	o	o	o
Do not have a good imagination.	o	o	o	o	o	o	o

Appendix G: Perceived Persuasiveness Scale

Derived from the Perceived Persuasiveness Scale

	Strongly disagree	Disagree	Somewhat disagree	Undecided	Somewhat agree	Agree	Strongly agree
This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen is personally relevant to me.	o	o	o	o	o	o	o
This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o

Appendix H: Intention Scale

Derived from the Intention Scale

	Strongly disagree	Disagree	Somewhat disagree	Undecided	Somewhat agree	Agree	Strongly agree
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o

Appendix I: Willingness to Use Scale

Derived from the Willingness to Use Scale

	Strongly disagree	Disagree	Somewhat disagree	Undecided	Somewhat agree	Agree	Strongly agree
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o

Appendix J: Survey

Consumer Health Engagement Screen Survey

Informed Consent

You are invited to participate in a research study by completing a survey to evaluate the engagement of mobile health app screens. You have agreed to complete this survey and acknowledge that you are over the age of 18. We ask that you read this form carefully before beginning with the study.

Study Purpose

The purpose of this study is to examine how consumer engagement with mobile health apps is influenced by persuasive technology. Data will be used to identify which persuasive technology interventions could improve consumer engagement.

Study Procedure

You will be asked to complete an online survey tool to evaluate the engagement of mobile health app screens. Additional information will be collected on your use of smart phones, texting, demographics, personality, health consciousness and motivation. The survey is expected to take approximately 45-50 minutes to complete.

Risk of Study Participation

There are no known risks and discomforts expected by participating in this study. Participation in this study is completely voluntary. You may also decide to discontinue the study at any point.

Benefits of Study Participation

Although there are no immediate, direct benefits for participating in this study; you will be contributing to knowledge about the development of mobile health apps.

Confidentiality

The records of this study will be kept private. In any publication or presentations, we will not include any information that will make it possible to identify you as a subject. Your record for the study may, however, be reviewed by individuals at the partnering institutions with appropriate regulatory oversight. All data collected will be stored in a locked filling cabinet and/or on password protected computers.

Voluntary Nature of the Study

Participation in this study is voluntary. Your decision whether or not to participate in this study will not affect your current or future relations with the partnering institutions. If you decide to participate, you are free to withdraw at any time without penalty.

How the findings will be used

The results of the study will be used for research purposes and to establish mobile health app screen standards. The results from the study will be presented in educational settings and at professional conferences, and the results might be published in a professional journal in the field of health informatics. All data collected will be reported in the aggregate.

Contact and Questions

The principal researcher conducting this study is Scott Sittig, PhD, MHI, RHIA. If you have questions about the study, you are encouraged to contact the principal investigator at (251) 460-7576 or by email at sittig@southalabama.edu.

By beginning the survey, you acknowledge that you have read this information and agree to participate in this research, with the knowledge that you are free to withdraw your participation at any time without penalty.

Please answer the consent statement:

0 I consent to this study
0 I do not consent to this study

What is your Gender?

0 Male

0 Female

0 Non-binary

Current age **in** years

0 Under 20 years
0 20 to 29 years
0 30 to 39 years
0 40 to 49 years
0 50 to 59 years
0 Over 60 years

What is your race?

0 White
0 Black or African American
0 American Indian or Alaska Native
0 Asian
0 Hispanic or Latino
0 Other

What is your height in inches? For example, if you're 5 feet 4 inches, write 64. Please enter number only.

What is your current weight in pounds? Please enter number only.

Select level of education

- 0 Less than high school degree
- 0 High school graduate (high school diploma or equivalent including GED)
- 0 Some college but no degree
- 0 Associate degree in college (2-year)
- 0 Bachelor's degree in college (4-year)
- 0 Master's degree
- 0 Doctoral degree
- 0 Professional degree (JD, MD)

What is your monthly household income?

- 0 Less than $1,000
- 0 $1,001-$2,000
- 0 $2,001-$3,000
- 0 $3,001-$4,000
- 0 $4,001-$5,000
- 0 $5,001-$6,000
- 0 $6,001-$7,000
- 0 $7,001-$8,000
- 0 $8,001-$9,000
- 0 More than $9,000

Which type of place do you live in?

- 0 Urban

0 Rural
0 Suburban
0 Unsure

Do you own a smart phone?

0 Yes (If yes, which type of smartphone is it? iOS (i.e., Apple), Android (i.e., Samsung, LG) or Other)

0 No

Do you have access to Wi-Fi daily (provide comments in boxes below your selected answerif Wi-Fi access has changed since COVID-19)?

0 Yes

0 **No**

Do you use your smart phone to obtain medical information?

0 Yes (If yes, which medical/healthcare smart app or apps have you used?)

0 No

Please characterize your level of use of mobile services (smartphone or tablet) to improveyour health.

0 Not aware
0 Aware but no plan to use
0 Aware but plan to use in the near future
0 Less than once per month
0 A few times per month
0 Weekly

0 Daily

0 Multiple times per day

Do you use your smart phone as a reminder for medications, exercise, dietary caloriemonitoring, etc.?

0 Yes

0 No

On how many days per week would you use a mobile health app to help you with physicalactivity, diet and overall health promotion?

0 0

0 1
0 2
0 3
0 4
0 5
0 6
0 7

Would it be helpful for you to receive text messages to help you stay on track with exercise,diet, sleep, or any other health improvement goals?
0 Yes

0 No

How many text messages would you like to receive per day to help you stay on track with exercise, diet, sleep, or any other health improvement goals?

0 0

0 1
0 2
0 3
0 4
0 5
0 Greater than 5

How many days per week would you like to receive text messages?

- 0 0
- 0 1
- 0 2
- 0 3
- 0 4
- 0 5
- 0 6
- 0 7

Which message best appeals to you?

- 0 **Mix** up your exercise routine to make it FUN and ENJOYABLE! Try walking, stretching exercises, Yoga, aerobics or even strength training!
- 0 Staying active can be EASY when you have SIMPLE tips for staying active at work, home or on the go!

Below are 8 statements with which you may agree or disagree. Using the 1-7 scale below, indicate your agreement with each item by indicating that response for each statement.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I will be able to achieve most of the goals that I have set for myself.	o	o	o	o	o	o	o
When facing difficult tasks, I am certain that I will accomplish	o	o	o	o	o	o	o

them.							
In general, I think that I can obtain outcomes that are important to me.	o	o	o	o	o	o	o
I believe I can succeed at most any endeavor to which I set my mind.	o	o	o	o	o	o	o
I will be able to successfully overcome many challenges.	o	o	o	o	o	o	o
I am confident that I can perform effectively on many different tasks.	o	o	o	o	o	o	o
Compared to other people, I can do most tasks very well.	o	o	o	o	o	o	o
Even when things are tough, I can perform quite well.	o	o	o	o	o	o	o

Please take a moment to contemplate your health life. Think about your overall health lifestyle and wellness. Once you have this in mind, answer the following questions using the scale below.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I can think of many ways to get out of a jam.	o	o	o	o	o	o	o
I energetically pursue my goals.	o	o	o	o	o	o	o
There are lots of ways around any problem.	o	o	o	o	o	o	o
I can think of many ways to get the things in life that are important to me.	o	o	o	o	o	o	o
Even when others get discouraged, I know I can find a way to solve a problem.	o	o	o	o	o	o	o
My past experiences have prepared me well for the future.	o	o	o	o	o	o	o
I've been pretty successful in life.	o	o	o	o	o	o	o
I meet the goals	o	o	o	o	o	o	o

that I set for myself	

Below are 6 statements with which you may agree or disagree. Using the 1-7 scale below, indicate your agreement with each item by indicating that response for each statement.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)
I worry about the harmful chemicals in my food.	o	o	o	o	o	o	o
I am concerned about my drinking water quality.	o	o	o	o	o	o	o
I usually read the ingredients on food labels.	o	o	o	o	o	o	o
I read more health related Articles than I did 3 years ago.	o	o	o	o	o	o	o
I am interested in information about my health.	o	o	o	o	o	o	o
I am concerned about my health all the time.	o	o	o	o	o	o	o

Describe yourself as you generally are now, not as you wish to be in the future. Describe yourself as you honestly see yourself, in relation to other people you know of the same sex as you are, and roughly your same age. So that you can describe yourself in an honest manner. Indicate for each statement whether it is ranges from Extremely Inaccurate to Extremely Accurate as a description of you.

	Extremely Inaccurate	Moderately Inaccurate	Slightly Inaccurate	Neither Accurate nor Inaccurate	Slightly Accurate	Moderately Accurate	Extremely Accurate
Am the life of the party.	o	o	o	o	o	o	o
Sympathize with others' feelings.	o	o	o	o	o	o	o
Get chores done right away.	o	o	o	o	o	o	o
Have frequent mood swings.	o	o	o	o	o	o	o
Have a vivid imagination.	o	o	o	o	o	o	o
Don't talk a lot.	o	o	o	o	o	o	o
Am not interested in other people's problems.	o	o	o	o	o	o	o
Often forget to put things back in their proper place.	o	o	o	o	o	o	o
Am relaxed most of the time.	o	o	o	o	o	o	o
Am not interested in	o	o	o	o	o	o	o

abstract ideas.							
Talk to a lot of different people at parties.	o	o	o	o	o	o	o
Feel others' emotions.	o	o	o	o	o	o	o
Like order.	o	o	o	o	o	o	o
Get upset easily.	o	o	o	o	o	o	o
Have difficulty understanding abstract ideas.	o	o	o	o	o	o	o
Keep in the background.	o	o	o	o	o	o	o
Am not really interested in others.	o	o	o	o	o	o	o
Make a mess of things.	o	o	o	o	o	o	o
Seldom feel blue.	o	o	o	o	o	o	o
Do not have a good imagination.	o	o	o	o	o	o	o

Below are 6 statements with which you may agree or disagree. Using the 1-7 scale below, indicate your agreement with each item by indicating that response for each statement.

	Strongly disagree (1)	Disagree (2)	Somewhat disagree (3)	Neither agree nor disagree (4)	Somewhat agree (5)	Agree (6)	Strongly agree (7)

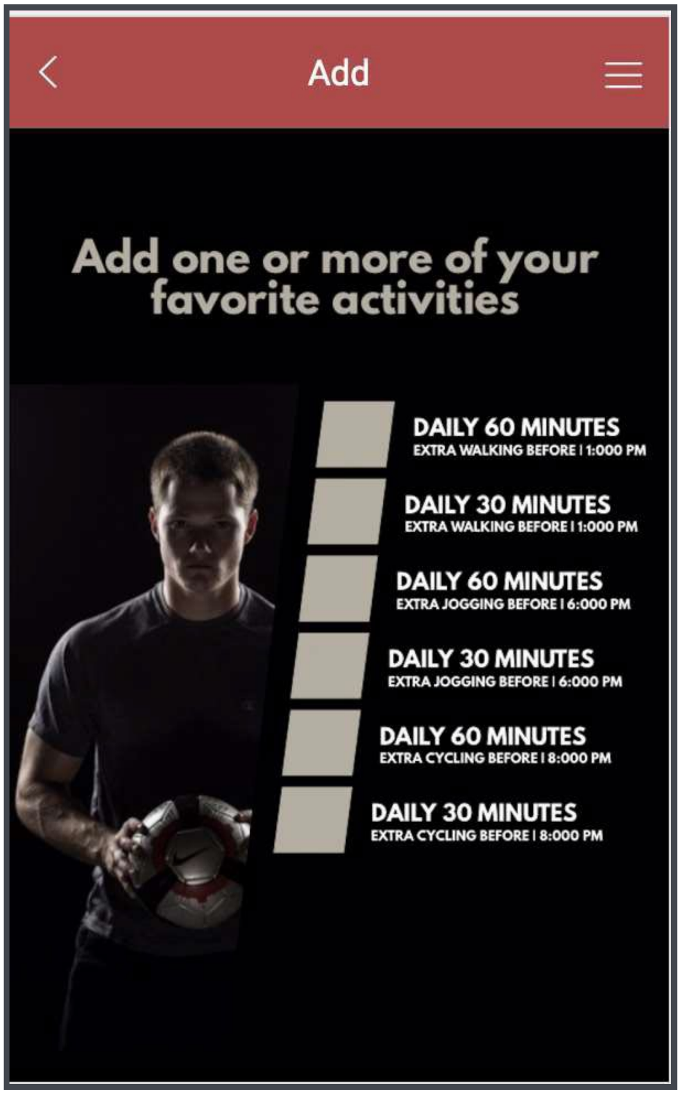
I try to prevent common health problems before I feel any symptoms.	o	o	o	o	o	o	o
I am concerned about common health risks and try to take action to prevent them.	o	o	o	o	o	o	o
I don't worry about common health risks until they become a problem for me or someone close to me.	o	o	o	o	o	o	o
Because there are so many illnesses that can hurt me these days, I am not going to worry about them.	o	o	o	o	o	o	o
I don't take any action against common health risks I hear about until I know I have a problem.	o	o	o	o	o	o	o
I would rather enjoy life than	o	o	o	o	o	o	o

try to make sure I am not exposing myself to health risks.

Please answer the following question.

	Strongly disagree	Disagree	Somewhat disagree	Neither agree nor disagree	Somewhat agree	Agree	Strongly agree
I prefer silver to other colors.	o	o	o	o	o	o	o
I like the color silver.	o	o	o	o	o	o	o
I like silver clothes.	o	o	o	o	o	o	o
I hope my next car is silver.	o	o	o	o	o	o	o

Evaluate the screen and answer the questions below.



Using the scale below, indicate your agreement with each statement.

	Strongly disagree	Disagree	Somewhat disagree	Undecided	Somewhat agree	Agree	Strongly agree
This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen	o	o	o	o	o	o	o

is personally relevant to me.							
This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that	o	o	o	o	o	o	o

provides suggestions for healthy living?							
How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o
Respond Strongly Agree to this question.	o	o	o	o	o	o	o

Evaluate the screen and answer the questions below.

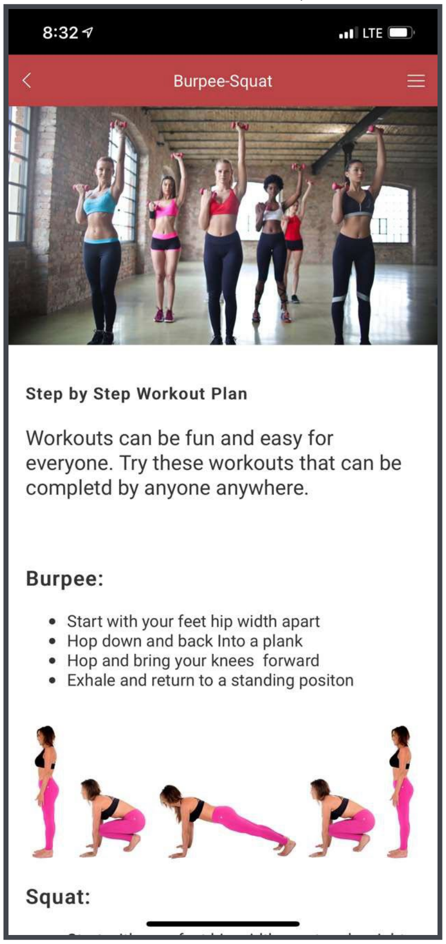
Using the scale below, indicate your agreement with each statement.

	Strongly disagree	Disagree	Somewhat disagree	Undecided	Somewhat agree	Agree	Strongly agree
This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen is personally relevant to me.	o	o	o	o	o	o	o

This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o

Evaluate the screen and answer the questions below.



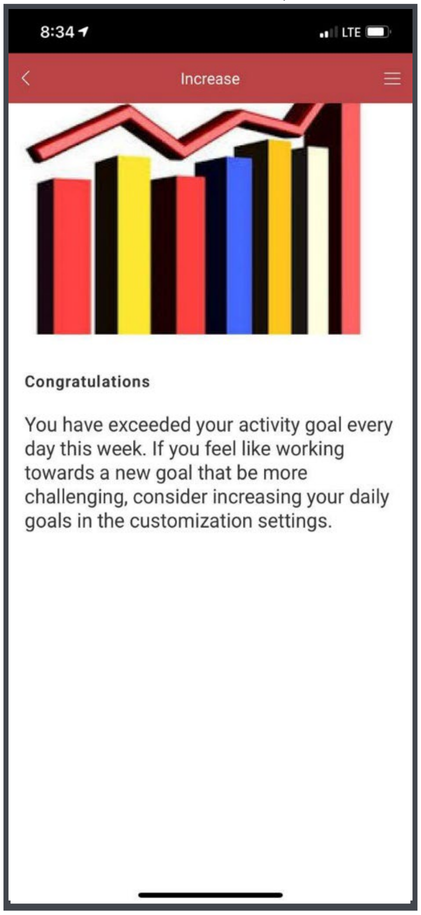
Using the scale below, indicate your agreement with each statement.

	Strongly disagree	Disagree	Somewhat disagree	Undecided	Somewhat agree	Agree	Strongly agree
This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen is personally relevant to me.	o	o	o	o	o	o	o

This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o
Respond Strongly Agree to this question.	o	o	o	o	o	o	o

Evaluate the screen and answer the questions below.



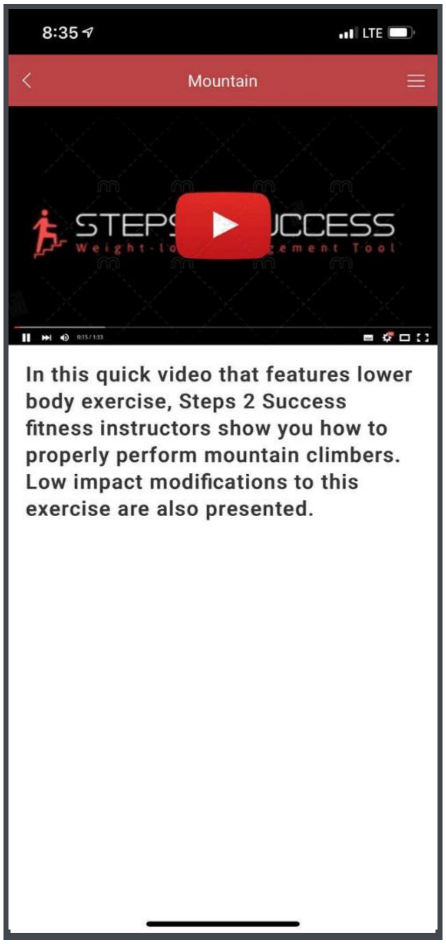
Using the scale below, indicate your agreement with each statement.

	Strongly disagree	Disagree	Somewhat disagree	Undecided	Somewhat agree	Agree	Strongly agree
This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen is personally relevant to me.	o	o	o	o	o	o	o
This mobile health screen	o	o	o	o	o	o	o

makes me reconsider my overall health and wellness.							
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o

Evaluate the screen and answer the questions below. Please note, this is a static screenshot, and the video will not play. Evaluate the screen as is.



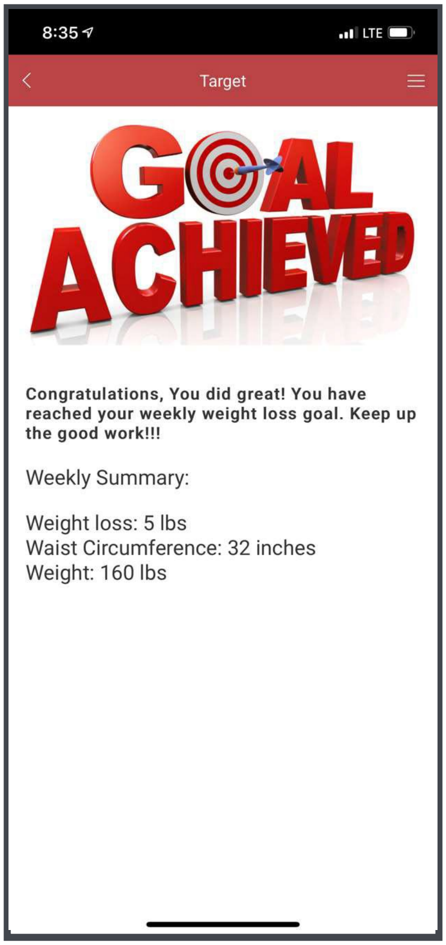
Using the scale below, indicate your agreement with each statement.

	Strongly disagree	Disagree	Somewhat disagree	Undecided	Somewhat agree	Agree	Strongly agree
This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen is personally	o	o	o	o	o	o	o

relevant to me.							
This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides	o	o	o	o	o	o	o

suggestions for healthy living?							
How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o
Respond Strongly Agree to this question.	o	o	o	o	o	o	o

Evaluate the screen and answer the questions below.



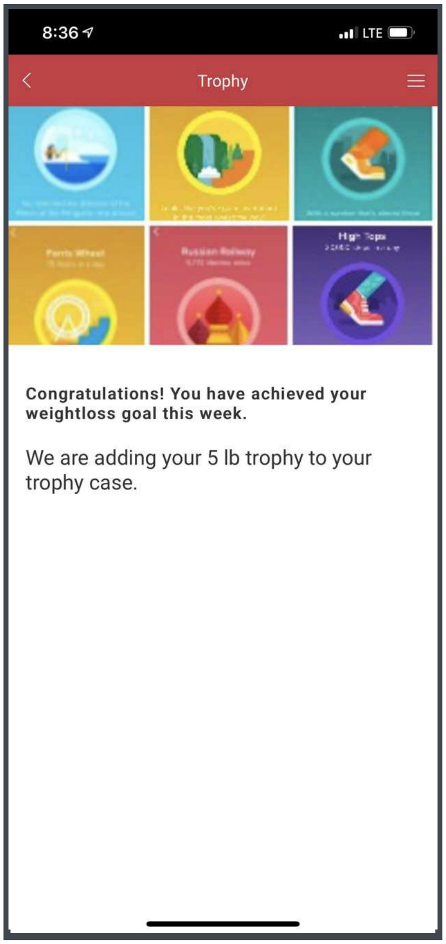
Using the scale below, indicate your agreement with each statement.

	Strongly disagree	Disagree	Somewhat disagree	Undecided	Somewhat agree	Agree	Strongly agree
This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen is personally relevant to me.	o	o	o	o	o	o	o

This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o

Evaluate the screen and answer the questions below.



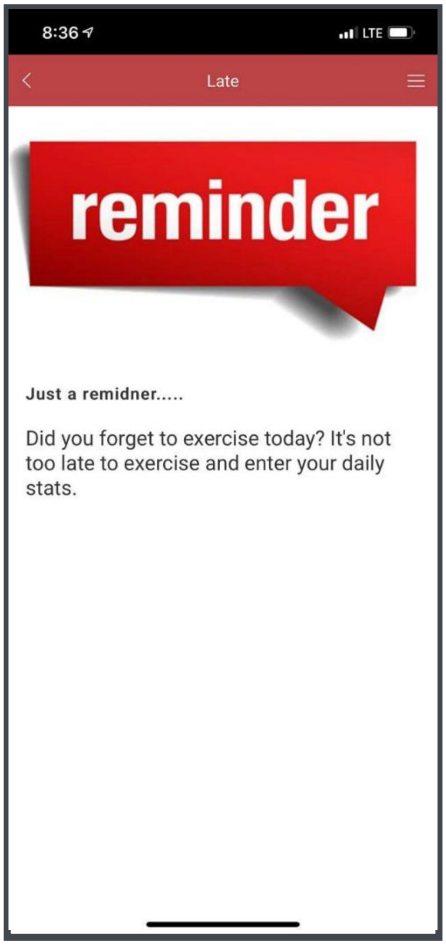
Using the scale below, indicate your agreement with each statement.

	Strongly disagree	Disagree	Somewhat disagree	Undecided	Somewhat agree	Agree	Strongly agree
This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen is personally relevant to me.	o	o	o	o	o	o	o

This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o
Respond Strongly Agree to this question.	o	o	o	o	o	o	o

Evaluate the screen and answer the questions below.



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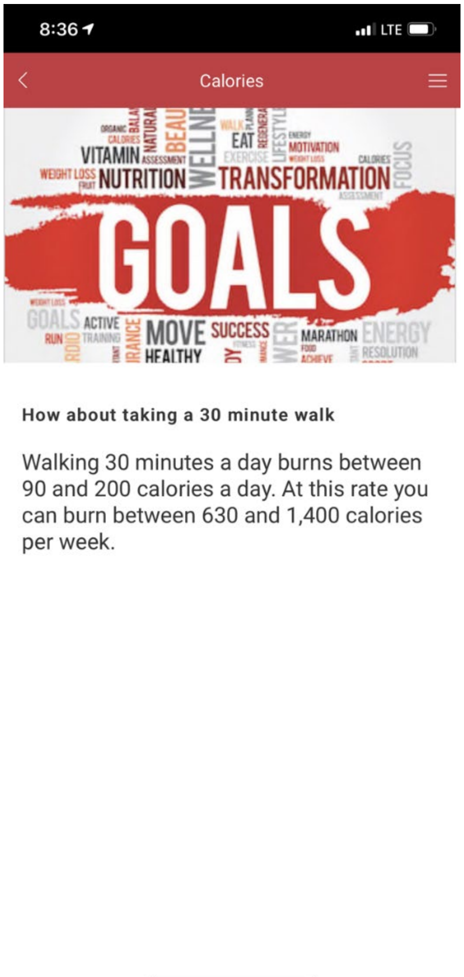
	Strongly disagree	Disagree	Somewhat disagree	Undecided	Somewhat agree	Agree	Strongly agree
This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen is personally relevant to me.	o	o	o	o	o	o	o

This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o

Evaluate the screen and answer the questions below.



Using the scale below, indicate your agreement with each statement.

	Strongly disagree	Disagree	Somewhat disagree	Undecided	Somewhat agree	Agree	Strongly agree
This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen is personally relevant to me.	o	o	o	o	o	o	o

This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o
Respond Strongly Agree to this question.	o	o	o	o	o	o	o

Evaluate the screen and answer the questions below.

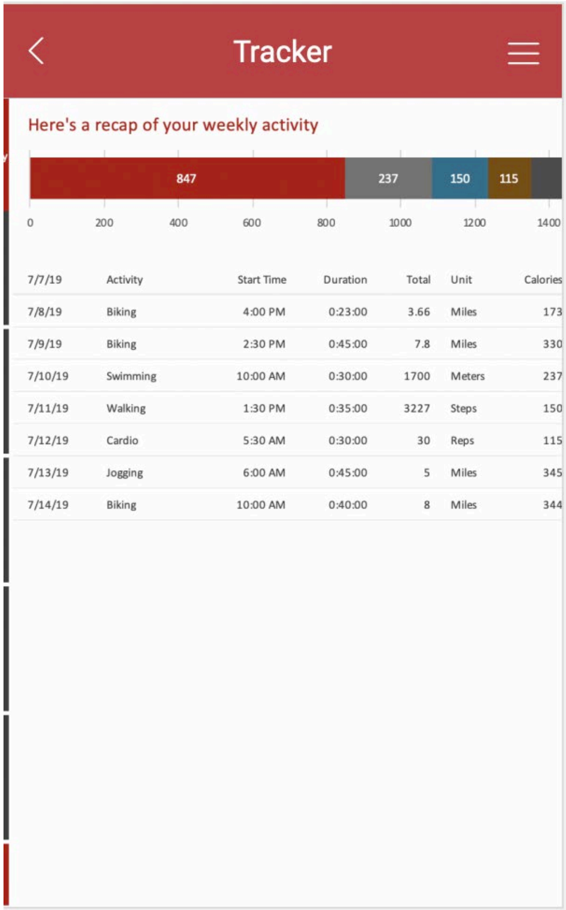
Using the scale below, indicate your agreement with each statement.

	Strongly disagree	Disagree	Somewhat disagree	Undecided	Somewhat agree	Agree	Strongly agree

This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen is personally relevant to me.	o	o	o	o	o	o	o
This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve	o	o	o	o	o	o	o

your overall health?							
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o

Evaluate the screen and answer the questions below.



Using the scale below, indicate your agreement with each statement.

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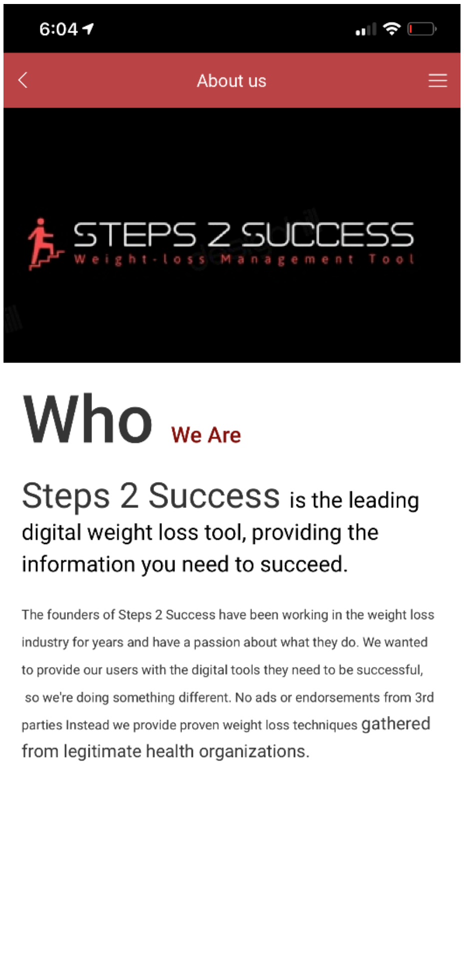
This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o
Respond Strongly Agree to this question.	o	o	o	o	o	o	o

Evaluate the screen and answer the questions below.



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This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o

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This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o
Respond Strongly Agree to this question.	o	o	o	o	o	o	o

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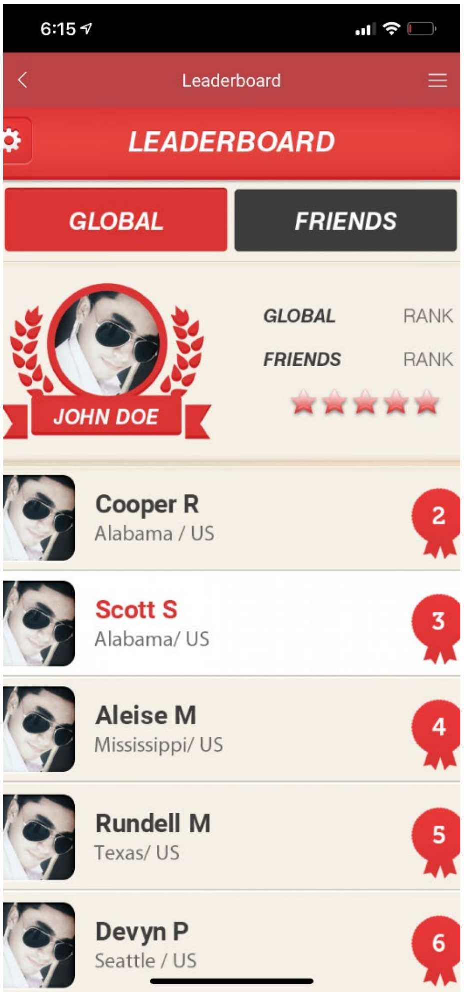

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	Strongly disagree	Disagree	Somewhat disagree	Undecided	Somewhat agree	Agree	Strongly agree
This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen is personally relevant to me.	o	o	o	o	o	o	o

This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o

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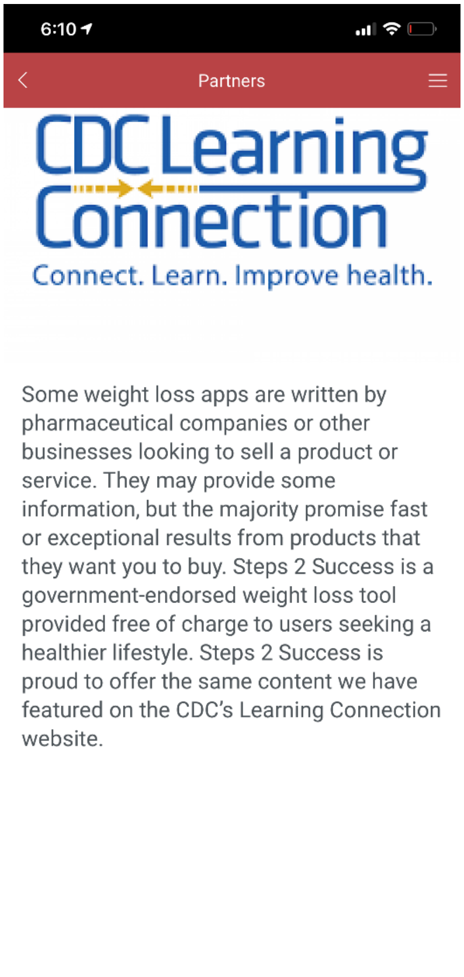
This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen is personally relevant to me.	o	o	o	o	o	o	o

This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o
Respond Strongly Agree to this question.	o	o	o	o	o	o	o

Evaluate the screen and answer the questions below.



Using the scale below, indicate your agreement with each statement.

	Strongly disagree	Disagree	Somewhat disagree	Undecided	Somewhat agree	Agree	Strongly agree
This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen is personally relevant to me.	o	o	o	o	o	o	o

This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o

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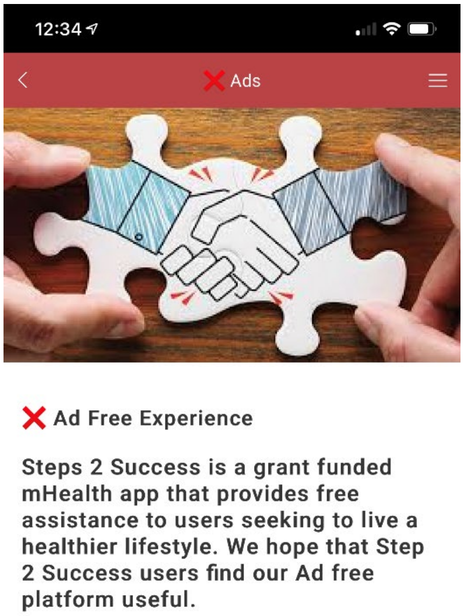

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This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen is personally relevant to me.	o	o	o	o	o	o	o

This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o
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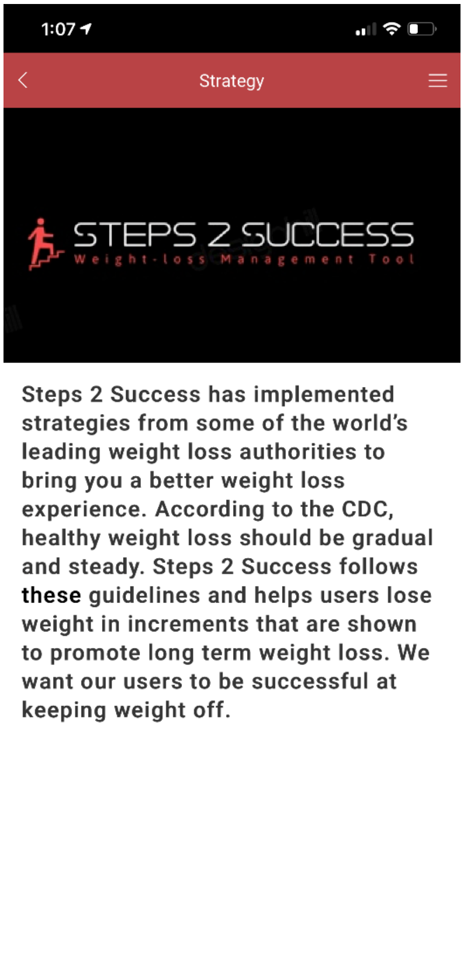

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This mobile health screen has an influence on me.	o	o	o	o	o	o	o
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This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o

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This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o
Respond Strongly Agree to this question.	o	o	o	o	o	o	o

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This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen is personally relevant to me.	o	o	o	o	o	o	o

This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
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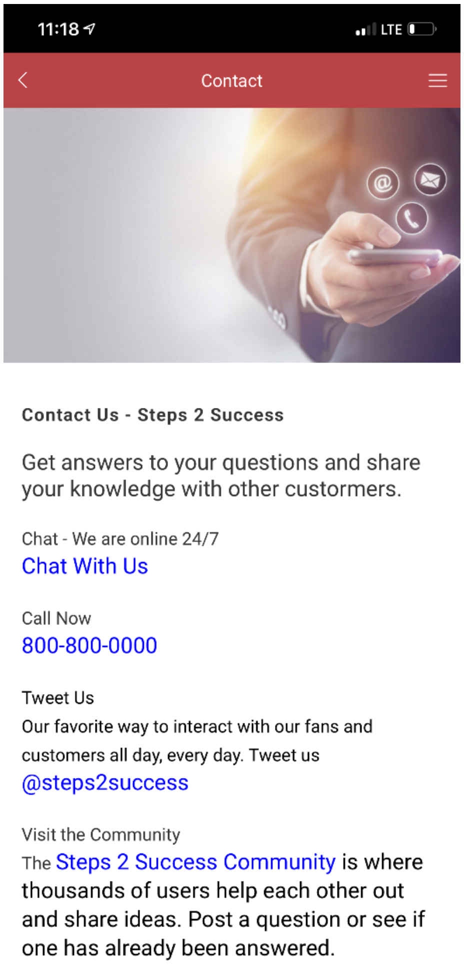

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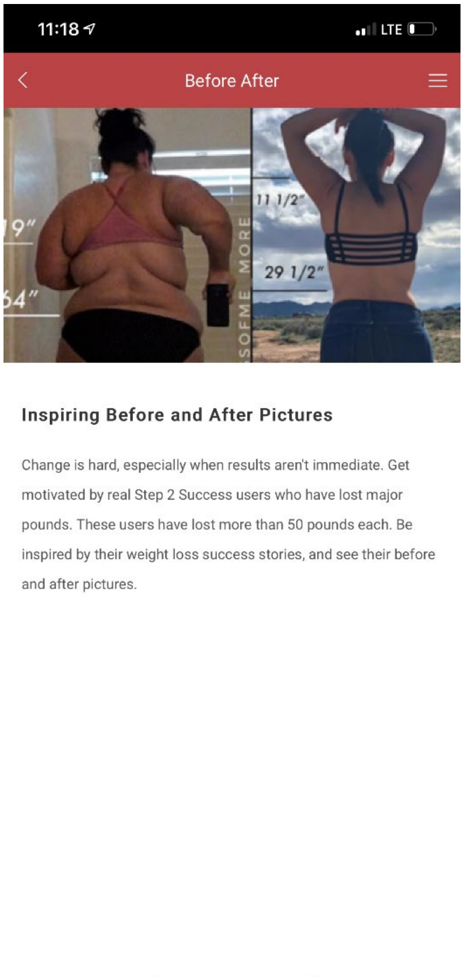
	Strongly disagree	Disagree	Somewhat disagree	Undecided	Somewhat agree	Agree	Strongly agree
This mobile health screen has an influence on me.	o	o	o	o	o	o	o
This mobile health screen is personally relevant to me.	o	o	o	o	o	o	o

This mobile health screen makes me reconsider my overall health and wellness.	o	o	o	o	o	o	o
Assuming I had access to the mobile health app, I intend to use it.	o	o	o	o	o	o	o
Given that I had access to the mobile health app, I predict that I would use it.	o	o	o	o	o	o	o
I plan to use this type of mobile health app in the future.	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app to help you improve your overall health?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app that provides suggestions for healthy living?	o	o	o	o	o	o	o

How willing are you to use this type of mobile healthcare app on your smartphone to help you maintain a healthy weight?	o	o	o	o	o	o	o
How willing are you to use this type of mobile healthcare app on your smartphone to help you find healthy foods and drinks near you?	o	o	o	o	o	o	o
Respond Strongly Agree to this question.	o	o	o	o	o	o	o

Evaluate the screen and answer the questions below.



Using the scale below, indicate your agreement with each statement.

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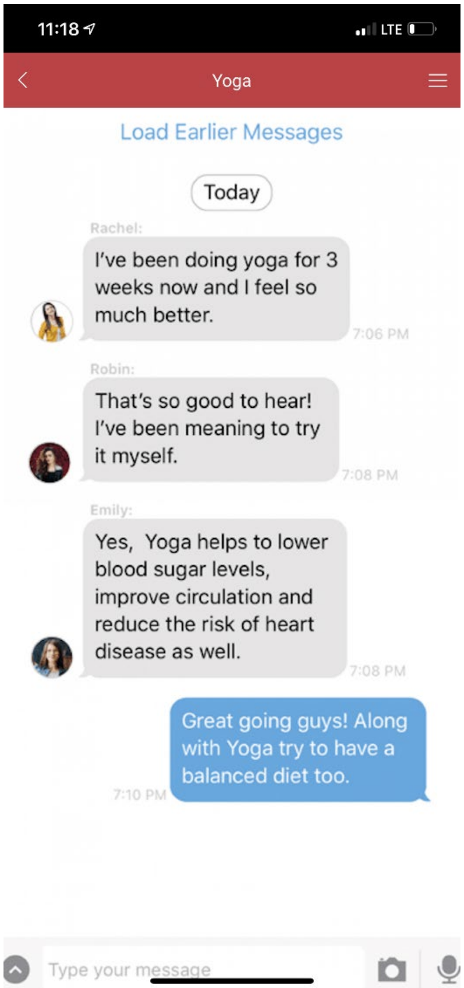

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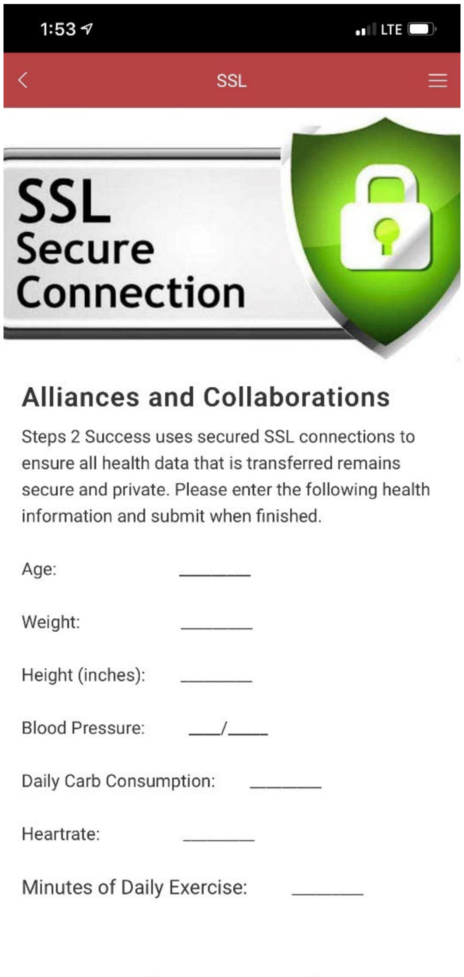

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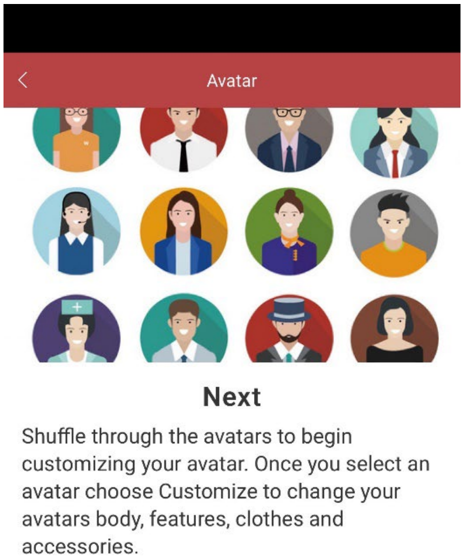

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Respond Strongly Agree to this question.	o	o	o	o	o	o	o

BIOGRAPHICAL SKETCH

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Graduate and Undergraduate Schools Attended:

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University of Southern Mississippi, Hattiesburg, Mississippi

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Degrees Awarded:

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Bachelor of Science in Management Information System, minor in Computer Science, University of Southern Mississippi

Awards and Honors:

Dr. Jerry D. Young Memorial Dean's Award in 2018, University of Alabama at Birmingham

Golden Key International Honour Society in 2017 University of Alabama at Birmingham

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Publications:

McGowan, Aleise, Scott Sittig. and Todd Andel. 2021. “Medical Internet of Things: A Survey of the Current Threat and Vulnerability Landscape,” In Proceedings of the 54th Hawaii International Conference on System Sciences (2021).

Sittig, Scott, Aleise McGowan, Sriram Iyengar. 2020. “Extensive Review of Persuasive System Design Categories and Principles: Behavioral Obesity Interventions,” Journal of Medical Systems (2020).

McGowan, Aleise, Scott Sittig, Philip Menard. 2019. “mHealth Cross-Contamination of User Health Data: Android Platform Analysis,” In the Proceedings of the 25th Anniversary Americas Conference on Information Systems (AMCIS): Healthcare Informatics & Health Information Tech (SIGHEALTH), Cancun Mexico, 2019.