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Theoretical Factors Associated with Real-time Use of an mHealth App Designed for HIV Self-management

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Doctor of Philosophy

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Abstract

Theoretical Factors Associated with Real-time Use of an mHealth App Designed for HIV Self-management

By Maya Grant Baumann

Background: Despite the ubiquity of mobile health (mHealth) apps, mobile phone users infrequently integrate them into their daily lives. Few empirical studies shed light on theoretical factors contributing to this lack of sustained interest.

Purpose: Guided by the modified Unified Theory of Acceptance and Use of Technology (UTAUT2), this secondary analysis of data from the Music for Health Project (MFHP) evaluated theoretical factors associated with the acceptance and adoption of a smartphone intervention app (iApp). The MFHP is an NIH/NINR-funded randomized control trial designed to test the efficacy of the iApp on antiretroviral therapy adherence and symptom/side effect self-management among rurally dwelling HIV-infected individuals.

Methods: The results of UTAUT2, smartphone experience (SPexp), and electronic health (eHealth) literacy surveys were compared with iApp usage among 34 MFHP participants in the first 100 days of the study. The SPexp survey was administered at baseline and measured how frequently common smartphone tasks were performed in the past three months. The other surveys were administered at baseline and three months. These measured UTAUT2 constructs (behavioral intention, effort expectancy, hedonic motivation, and performance expectancy) and eHealth literacy (confidence finding/using Internet-based health information). Usage metrics included frequency of iApp openings and duration of time spent in the app.

Findings: At baseline and three months, most scored at or near the highest attainable in all surveys. UTAUT2 subscales, eHealth literacy, and SPexp were positively intercorrelated with each other (all $p \leq .05$) but not with frequency or duration of iApp usage. Younger participants scored the highest in the UTAUT2 survey, indicating the most intent to adopt mHealth apps and reporting stronger beliefs that mHealth apps could be easy to use, enjoyable, and helpful to maintain health (all $p < .025$). Forty-one percent did not open the iApp - these were typically newly diagnosed with HIV less than six months prior to entering the MFHP ($p < .025$). Among those who opened the app, frequency and duration of use peaked in the first four weeks, then declined to almost zero over the next eleven weeks.

Discussion: Findings suggest that MFHP participants' intention to adopt mHealth does not necessarily translate into initial or sustained action. Moreover, a "one-app-fits-all" approach might not be the most effective way to improve disease self-management equally among all HIV-positive patients. Newly diagnosed individuals may require a different mHealth approach to foster engagement-in-care and facilitate effective self-management behavior.

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I dedicate this work to the memory of my mother**, Carmen Filteau Grant**, a mathematician, and my grandmother, **Anna Vœlker Grant**, a nuclear engineer. Both taught me by word and by action that women have valuable contributions to make in the sciences.

Acknowledgements

My deepest gratitude to Dr. Marcia M. Holstad, my advisor and committee chair. Through steadfast support and gentle guidance, she enabled me to sharpen my research skills. Heartfelt thanks to the rest of my committee, Dr. Melinda Higgins, Dr. Seth Himelhoch, and Dr. Drenna Waldrop-Valverde. They believed I had what it took to complete this journey and encouraged me to persevere in hardship. Without their keen input and thoughtful critiques, I could not have pulled this dissertation together into a cohesive whole. I feel blessed to have had each of these gifted researchers on my committee.

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Finally (but most importantly), I thank God for giving me the ability to finish my doctoral studies. Without His blessings and constant presence in my life, none of this could ever have been possible.

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Abbreviations

ACASI	Audio computer-assisted self-interview
AIDS	Acquired immune deficiency syndrome
App	Application
ART	Antiretroviral therapy
BI	Behavioral intention
EE	Effort expectancy
eHEALS	eHealth Literacy Scale
eHealth	Electronic health
EHR	Electronic health record
GDPH	Georgia Department of Public Health
HIT	Health information technology
HIV	Human immunodeficiency virus
HM	Hedonic motivation
iApp	Intervention application
IT	Information technology
MASS	Mobile app stickiness
MFHP	Music for Health Project
mHealth	Mobile health
MMS	Multimedia messaging service
PE	Performance expectancy
PLWHA	Persons living with HIV/AIDS
RCT	Randomized control trial
SMS	Short message service
Spexp	Smartphone Experience Questionnaire
UTAUT2	Modified Unified Theory of Acceptance and Use of Technology

CHAPTER 1

INTRODUCTION

Since the early 2000s, the mobile ecosystem (i.e., the complex array of wireless, or cellular networks) has grown into a dominant technology within the United States. An estimated 90% of Americans own cellular (cell) phones, nearly two-thirds of which are smartphones (Pew Internet & American Life Project, 2014; Smith, 2015). Ever-evolving network capabilities and near instantaneous mobile Internet connectivity have facilitated a surge in both consumer health information-seeking and personal health tracking (e.g., Fitbit, MyFitnessPal, MapMyFitness) as among the fastest growing wireless content categories (comScore, 2012, 2015; Krebs & Duncan, 2015). In 2015, approximately 62% of smartphone owners accessed health information on their wireless phones (Smith, 2015). Concomitantly, about 58% of users downloaded at least one health-related application software (app) onto their smartphones, a nearly 40% increase from 2012 (Fox & Duggan, 2012; Krebs & Duncan, 2015). This burgeoning interest in health content roughly coincides with an increasing, almost exclusive reliance on wireless telephones as the primary means of communication and internet access among minority and low-income persons, many of whom suffer comorbid chronic diseases and experience barriers to healthcare access (Blumberg, Ganesh, Luke, & Gonzales, 2013; Smith, 2015). Thus, the ubiquity of mobile technology and growing public interest in health-related content make mobile health (mHealth) a desirable platform upon which to develop interventions aligned with national health care objectives: widening patient outreach, reducing costs, and improving long-term outcomes (U.S. Department of Health & Human Services, 2014).

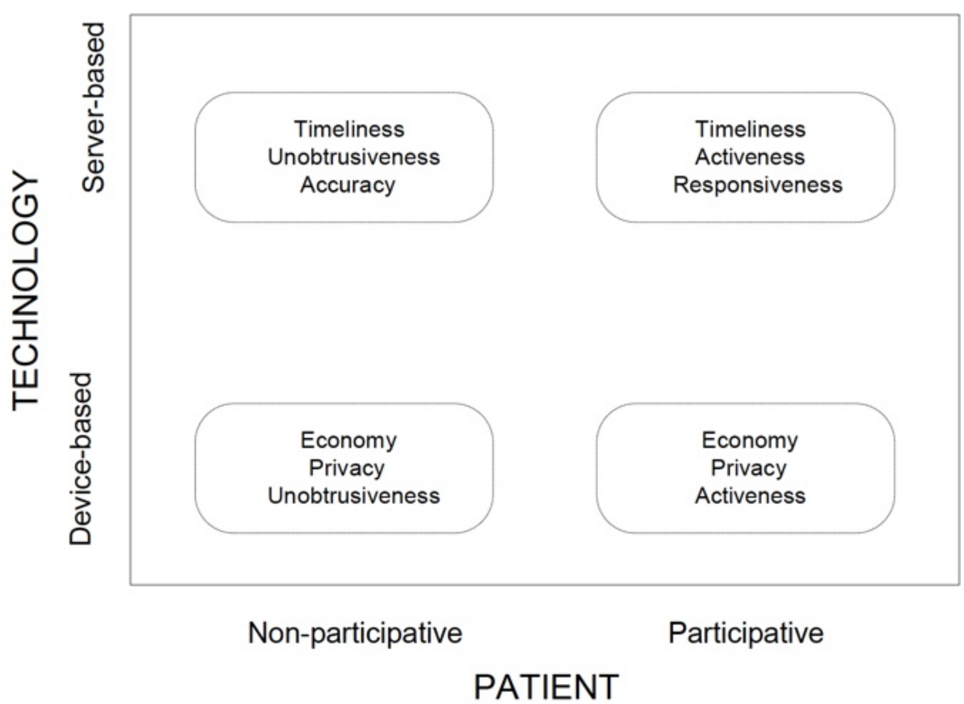
Despite the growing popularity of mHealth content, a comparatively small number of wireless users consistently integrate mHealth apps into their daily routines. In a survey of 1600 smartphone users, Krebs and Duncan (2015) found that only 12% of respondents regularly used an mHealth app to track and/or manage their health, and almost half of users who initially downloaded health apps stopped using them on their phones. The authors surmised that developers' failure to accommodate user preferences may significantly contribute to consistently low adoption rates. Reasons commonly cited by survey respondents for discontinuing app use lend credence to these speculations: complicated/confusing interface, loss of interest, privacy concerns and cost.

Few empirical studies have focused on factors affecting the acceptance and use of mHealth interventions from a patient perspective, possibly because health apps – most of which are commercially available – are seldom designed keeping consumer needs in mind or employing evidence-based science (Krebs & Duncan, 2015; Samhan, Dadgar, & Joshi, 2013). This study attempted to fill that gap by evaluating the theoretical factors influencing the acceptance and adoption, including usage, of an mHealth app that integrates a music-based simulated "talk radio" program, interactive resource manual, and music videos into a single device-based application (app). This was a sub-study of the Music for Health Project (MFHP), an NINR/NIH-funded randomized control trial (RCT) to examine the efficacy of an mHealth app designed to improve antiretroviral (ART) adherence and symptom self-management among HIV-positive patients in ambulatory HIV clinics throughout rural Georgia.

Statement of the Problem

Cocosila and Archer (2005) postulated that the unique nature of mHealth creates a dilemma integrating both user and technology, giving rise to two extremes involving the extent of user participation and technology capability. Figure 1 represents a matrix of technology and user options available for mHealth monitoring. In this context, user participation ranges from fully participative to fully non-participative interactions. Fully participative interactions employ active task completion, communication, and feedback. The quality of interaction is influenced by user characteristics, such as knowledge and skills. Fully non-participative interactions are passive and require no user input. In addition, technology can extend from server-based to device-based capabilities. Server-based technologies instantaneously monitor progress by uploading information wirelessly to remote databases, allowing for closer patient monitoring and faster feedback. As opposed to communicating with remote servers, device-based technologies collect and store data locally on a mobile device. This approach limits sharing sensitive information to only a few people. Unlike more static electronic information systems (e.g., computer-based programs), the success of mHealth adoption depends on the right combination of user participation and technological capability.

Figure 1. Patient and technology interactions in mHealth monitoring



Note. Adapted from "A framework for mobile healthcare answers to chronically ill outpatient non-adherence," by M. Cocosila and N. Archer, 2005, *Informatics in Primary Care, 13*(2), p. 151.

In the continuum of alternatives presented in Figure 1, identifying predisposing user preferences underlying technology acceptance is crucial to striking the optimal balance necessary to engender repeat usage (Cocosila & Archer, 2005, 2010). For example, some individuals may be motivated to engage in health maintenance by revisiting and spending time on an innovative, interactive mHealth application. Others may be hesitant to use mHealth technology because of perceived intrusiveness, effort intensity, or cost. Hence, an understanding of the target population's needs, concerns and desires is paramount when creating a sustainable mHealth intervention.

While researchers recognize that user (e.g., patient) preferences are critical to integrate innovative technologies into disease self-management, the question remains: which aspects of acceptance are most important to mHealth adoption? Venkatesh, Thong, and Xu (2012) conceptualized consumer-oriented technology acceptance as a multidimensional construct in which behavioral intent, the main influence of action, forms the centerpiece. Within that framework, core interpersonal factors act as antecedents to behavioral intent. Of these, performance expectancy (perceived benefits related to technology use) and effort expectancy (perceived ease of operation) significantly contribute to the acceptance and use of health information technology (HIT). Both have been identified as key motivators of consumer adoption of electronic health record patient portals (Tavares & Oliveira, 2016), clinicians' adoption of health information systems (Holden & Karsh, 2010), heart failure patients' satisfaction with telemedicine services (Kraai, Luttik, de Jong, Jaarsma, & Hillege, 2011), and chronically ill patients' use of technology-assisted home care (Or et al., 2011). Emerging evidence also indicates that hedonic motivation (perceived enjoyment), a seldom-studied variable in mHealth acceptance, is an equally significant contributor to behavioral intent and subsequent usage. When examining perceived enjoyment on consumer-level technology adoption, Dickinger, Arami, and Meyer (2008) and Van der Heijden (2004) found that hedonic motivation even surpassed performance expectancy as a key motivator of behavioral intent. Consequently, as more mHealth interventions foster health through entertainment, hedonic motivation may play a prominent role in patient acceptance.

Of existing HIT research, a surprisingly low percentage examines the potential contributions of moderating conditions to user adoption. For example, the Institute of Medicine (2009) identified poor eHealth literacy – the ability to find, evaluate, and use health information from electronic sources – as a major contributor to health disparities arising from the "digital divide" between those who use HIT and those who do not. Yet, few studies have focused on the impact of eHealth literacy on consumer use of information technology. A recent systematic review found only 44 articles published since 2010 that specifically investigated e-health literacy within the context of web-based or app-based interventions (Kim & Xie, 2015). Similarly, the behavioral effects of individual characteristics on technology use have not been explicated in the realm of health information systems. Venkatesh et al. (2012) reported that users' technology experience moderated the relationships between interpersonal factors (e.g., performance expectancy, effort expectancy, and hedonic motivation) and behavioral intention. Theoretically, technology experience will enhance motivational precursors to intent and use of an information technology; however, little research has focused on the influence of technology experience on factors specifically affecting mHealth acceptance.

Purpose of the Study

This study examined the antecedent influences of performance expectancy, effort expectancy, and hedonic motivation on behavioral intent-to-use and actual use of the MFHP smartphone intervention app (iApp), which was designed to encourage disease self-management and ART adherence among rural-dwelling HIV-positive persons. Additionally, eHealth literacy and smartphone experience were explored for their moderating effects on behavioral intent and subsequent usage. Performance expectancy, effort expectancy, and hedonic motivation were hypothesized to influence use of the MFHP app by increasing behavioral intent, the primary determinant of usage behavior. Low eHealth literacy and minimal smartphone experience were presumed to negatively impact behavioral intent and usage; therefore, both were expected to moderate the relationships between antecedent variables and behavioral intention. This is one of the first studies examining real-time use of an mHealth intervention within the context of technology acceptance and eHealth literacy. Research aims, questions and related hypotheses (H) are as follows:

Aim 1: Examine the associations between antecedent effects (performance expectancy, effort expectancy, and hedonic motivation) and behavioral intent to use the MFHP iApp.

Question 1: Are performance expectancy, effort expectancy, and hedonic motivation associated with behavioral intent to use the MFHP iApp?

H1-A: Performance expectancy has a direct positive association with behavioral intent to use the MFHP iApp.

H1-B: Effort expectancy has direct positive association with behavioral intent to use the MFHP iApp.

H1-C: Hedonic motivation has a direct positive association with behavioral intent to use the MFHP iApp.

Aim 2: Determine the association between behavioral intent and MFHP iApp usage (number of times the app is accessed; amount of time spent using the app).

Question 2: Is behavioral intent associated with the number of times the MFHP iApp is accessed?

H2: Behavioral intent will be positively associated with the number of times MFHP iApp is accessed. Increased behavioral intent to use the MFHP iApp will result in a higher frequency of MFHP iApp access.

Question 3: Is behavioral intent associated with the amount of time spent using the MFHP iApp?

H3: Behavioral intent will be positively associated with the amount of time spent using the MFHP iApp. Increased behavioral intent to use the MFHP iApp will result in a longer duration of time spent using the MFHP iApp.

Aim 3: Examine the moderating effects of smartphone experience and eHealth literacy on the relationships between antecedents and behavioral intention.

Question 4: Do eHealth literacy and smartphone experience moderate the relationship between behavioral intent antecedents (performance expectancy, effort expectancy, and perceived enjoyment) and behavioral intent?

H4-A: eHealth literacy moderates the association between behavioral intent antecedents and behavioral intention. The association with behavioral intent will be diminished in the presence of low eHealth literacy.

H4-B: Smartphone experience moderates the association between behavioral intent antecedents and behavioral intention. Smartphone inexperience will weaken the association between the antecedents and behavioral intent.

Theoretical Framework

The following section will present an overview of the theoretical model framing this study. In addition, relevant constructs will be briefly defined; however, a more in-depth discussion of these variables is presented in Chapter 2.

Modified Unified Theory of Acceptance and Use of Technology

The Modified Unified Theory of Acceptance and Use of Technology (UTAUT2) provided the framework for this research. Originally developed to explain technology adoption on an organizational level, the first iteration of this model, UTAUT, was distilled from eight established user acceptance theories: Theory of Reasoned Action, Technology Acceptance Model, Motivational Model, Theory of Planned Behavior, a Combined Theory of Planned Behavior/Technology Acceptance Model, Model of Personal Computer Use, Diffusion of Innovations Theory, and Social Cognitive Theory (Venkatesh, Morris, Davis, & Davis, 2003). Since its inception, UTAUT has been used for a variety of health technology applications, such as explaining clinicians' adoption of electronic medical records systems (Venkatesh, Sykes, & Zhang, 2011), contextualizing physicians' beliefs regarding robotic-assisted surgery (BenMessaoud, Kharrazi, & MacDorman, 2011), and understanding patient acceptance of consumer health information technology (Or & Karsh, 2009).

To capture behavioral intent and usage of emerging technologies in a consumer-driven context, UTAUT was later extended into UTAUT2 by adding user-centered constructs to the model: hedonistic motivation, price value, and habit (Venkatesh et al., 2012). UTAUT2 posits that performance expectancy, effort expectancy, price value, habit, and hedonic motivation are antecedent conditions that directly influence behavioral intent to use technology, which subsequently affects usage behavior. In an examination of factors contributing to consumer adoption of a mobile Internet technology, Venkatesh et al. (2012) found that these relationships accounted for 74% of the variance explained for behavioral intention and 52% of technology use. UTAUT2 has also been used to explain undergraduate students' acceptance of mobile learning (Kang, Liew, Lim, Jang, & Lee, 2015; Yang, 2013) and social network gaming behavior (Xu, 2014). Within the context of HIT, UTAUT2 was used to identify key factors driving the acceptance of electronic health record portals (Tavares & Oliveira, 2016) and to examine predictors of users' intentions to adopt health and fitness apps (Yuan, Ma, Kanthawala, & Peng, 2015)

Key Constructs

Figure 2 illustrates this study conceptualized within the UTAUT2 framework. (Note: because the MFHP research participants are supplied with smartphones and cellular service, price value and habit constructs were omitted.) Antecedent conditions – performance expectancy, effort expectancy, and hedonic motivation – directly influence the behavioral intent to use the MFHP app. In turn, behavioral intent is assumed to determine the outcome, which is the actual use of the intervention. Smartphone experience and eHealth literacy affect MFHP usage by moderating the relationship between antecedents and behavioral intent. Operational definitions of key constructs are as follows:

Performance expectancy. Performance expectancy is the amount of benefit, or gain, users expect to derive from a technology (Venkatesh et al., 2012). In the context of this study, performance expectancy indicates the degree to which MFHP participants find the smartphone app beneficial in the promotion of symptom self-management and ART adherence.

Effort expectancy. Effort expectancy is the perceived ease, or effortlessness, associated with using a technology (Venkatesh et al., 2003; Venkatesh et al., 2012). Higher effort expectancy indicates greater ease. For this study, effort expectancy refers to the ease with which MFHP participants access and operate the smartphone app.

Hedonic motivation. Hedonic motivation is the pleasure, or enjoyment, experienced by using a technology (Venkatesh et al., 2012). In this study, hedonistic motivation refers to the entertainment value of the music and video components of the MFHP smartphone app.

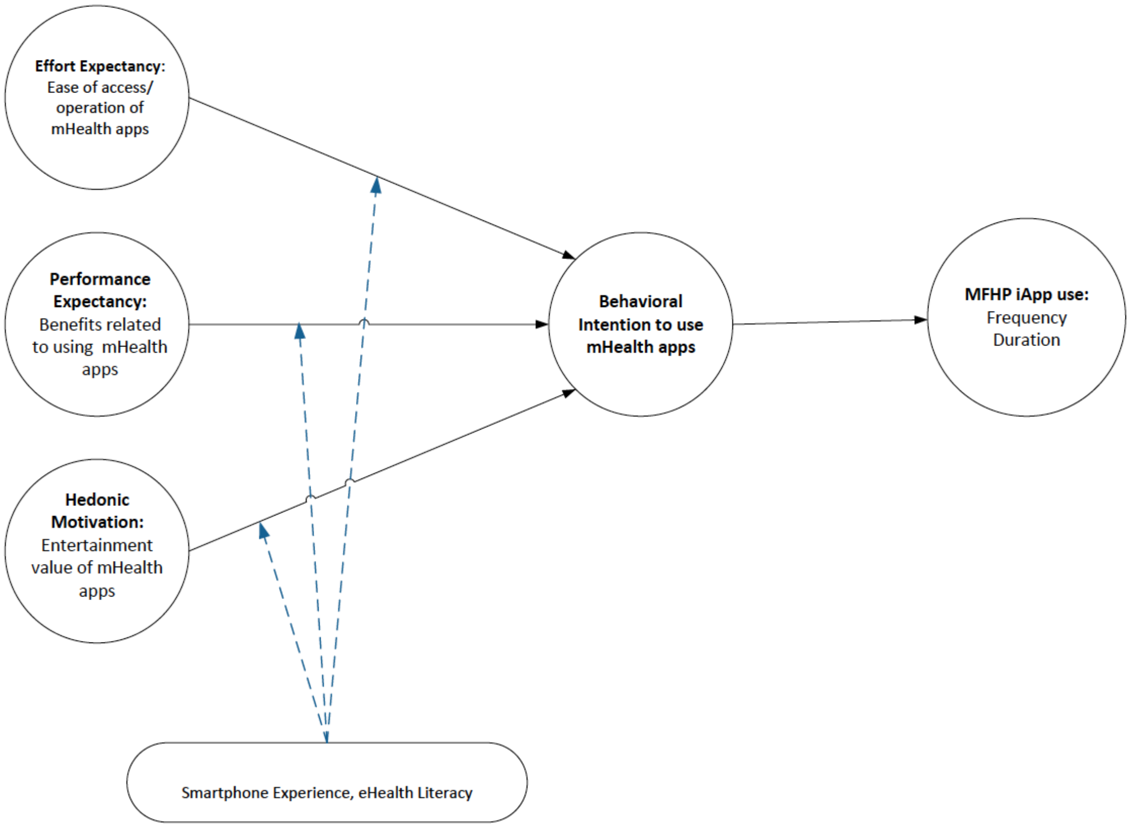
Smartphone experience. Venkatesh et al. (2012) conceptualized experience as opportunities to use a technology over the passage of time since its initial use. Thus, increased exposure may be positively associated with the intention to adopt the technology for routine usage. For this study, experience is operationalized as the frequency in which smartphone features (music, videos, applications, and Internet access) have been used in the past 3 months.

eHealth literacy. Norman and Skinner (2006a) define eHealth literacy as "the ability to seek, find, understand, and appraise health information from electronic sources and apply the knowledge gained to addressing or solving a health problem." Within the context of this study, eHealth literacy is the MFHP participant's ability to research/evaluate/use web-based health information.

Behavioral intention. Venkatesh et al. (2003) define behavioral intent as the user's intention to engage in a technology-specific action. For this study, behavioral intent is operationalized as the MFHP participant's intention to use the smartphone intervention.

MFHP app use. MFHP app use is operationalized as the number of times the app is accessed during a specified period (frequency) and the duration of time (in seconds) spent using the app with each access. "Actual use" is not a self-report measure; rather, it is quantified through real-time Flurry analytics over the course of the study.

Figure 2. Conceptual model for the current study



CHAPTER 2

LITERATURE REVIEW

This chapter examines the origins of the modified Unified Theory of Acceptance and Use of Technology (UTAUT2) and its contribution to health information technology (HIT) research. Specifically, the relationships between each of the antecedent constructs (performance expectancy, effort expectancy, and hedonic motivation) and outcomes (behavioral intent and technology usage) are described. In addition, the moderating influences of eHealth literacy and technology experience on behavioral intent are discussed. Content is organized into the following sections: 1) UTAUT2 overview, 2) behavioral outcomes, 3) behavioral intention antecedents, 4) moderating influences, and 5) conclusions.

UTAUT2 Overview

Unified Theory of Acceptance and Use of Technology (UTAUT)

UTAUT – and by extension UTAUT2 – increases the explanatory power of users' technology adoption intentions by aggregating principle concepts contained within prominent behavioral acceptance models. This framework arose from Venkatesh, Morris, Davis and Davis' (2003) observations that the field of acceptance research is saturated with competing theories, forcing researchers to single out constructs across models or to rely on a single "favored" model to the exclusion of other perspectives. Venkatesh and colleagues argued that a synthesis of extant user theories would provide a better global understanding of factors influencing technology acceptance, especially in organizations with policies mandating information technology (IT) use. To that end, they sought to unify multiple, seemingly disparate, theories into a single, cohesive whole.

After analyzing and synthesizing eight major user models (Table 1), Venkatesh et al. (2003) developed the UTAUT framework. Based on a comprehensive review of user acceptance literature and an empirical (i.e., formally studied) comparison of these models, four constructs – performance expectancy, effort expectancy, social influence, and facilitating conditions – were hypothesized to directly affect behavioral intention. In turn, behavioral intention was postulated to directly affect technology usage. Moreover, four moderating factors that historically improved the predictive capabilities in all but two of the previous models (MM, SCT [Table 1]) were added to the unified framework: voluntariness, experience, age, and gender. Two longitudinal field studies of the final model, both of which pooled data collected from various business settings, revealed that elements within UTAUT accounted for about 70% of variance in technology usage intention and about 50% of the variance in technology use. Venkatesh et al. concluded that UTAUT furnishes insight into the consistency of the association between intention and behavior.

Table 1

Theoretical models from which UTAUT was derived

Abbreviation	Theoretical Model
DOI	Diffusion of Innovations
MM	Motivational Model
MPCU	Model of Personal Computer use
SCT	Social Cognitive Theory
TAM	Technology Acceptance Model
TAM-TPB	Combined Technology Acceptance Model/Theory of Planned Behavior
TPB	Theory of Planned Behavior
TRA	Theory of Reasoned Action

UTAUT in HIT research. Since its development, UTAUT has successfully transitioned into health research settings, especially in conjunction with providers' acceptance and use of specific HIT applications. Several studies have utilized the UTAUT framework to examine factors affecting clinicians' satisfaction with and acceptance of new electronic medical records systems (Alapetite, Boje Andersen, & Hertzum, 2009; Chisolm, Purnell, Cohen, & McAlearney, 2010; Venkatesh et al., 2011), understand the utilization of clinical decision support systems (Chang, Hwang, Hung, & Li, 2007; Ifinedo, 2012; Kijsanayotin, Pannarunothai, & Speedie, 2009) and to identify barriers affecting the adoption of a Picture Archiving and Communication System by radiologists (Duyck et al., 2010). Although a large percentage of UTAUT-based literature focuses on medical professionals, some research also focuses on patient acceptance and adoption of novel technologies (Or et al., 2011). In general, these studies, mostly cross-sectional, demonstrated significant associations between antecedent conditions and behavioral intentions. The one study that employed a longitudinal design showed a small-to-moderate positive relationship between behavioral intention and technology usage (Venkatesh et al., 2011).

Modified Unified Theory of Acceptance and Use of Technology (UTAUT2)

Despite its success predicting technology adoption within organizational contexts, UTAUT has not been as robust when applied to consumer contexts (Venkatesh et al., 2012). Whereas employees implement new technologies for job-related or performance-based gains, consumer behaviors are driven by a different set of considerations, such as practicality, enjoyment, and value (Brown, Massey, Montoya-Weiss, & Burkman, 2002; Childers, Carr, Peck, & Carson, 2001; Venkatesh et al., 2003). Hence, employee motivations to adopt innovative technologies cannot be considered analogous to those of the consumer (Venkatesh et al., 2012).

Table 2

UTAUT2 construct definitions

Construct	Definition
Performance Expectancy*	The degree to which using a technology will provide benefits to consumers in performing certain activities
Effort Expectancy*	The degree of ease associated with the use of the system
Social Influence	The extent to which consumers perceive that important others (e.g., family and friends) believe they should use a technology
Facilitating conditions	Consumers' perceptions of the resources and support available to perform a behavior
Hedonic Motivation*	Users perceptions of fun or pleasure derived from using a technology
Price Value	Consumers' cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them
Habit	The extent to which people tend to perform behaviors automatically because of learning

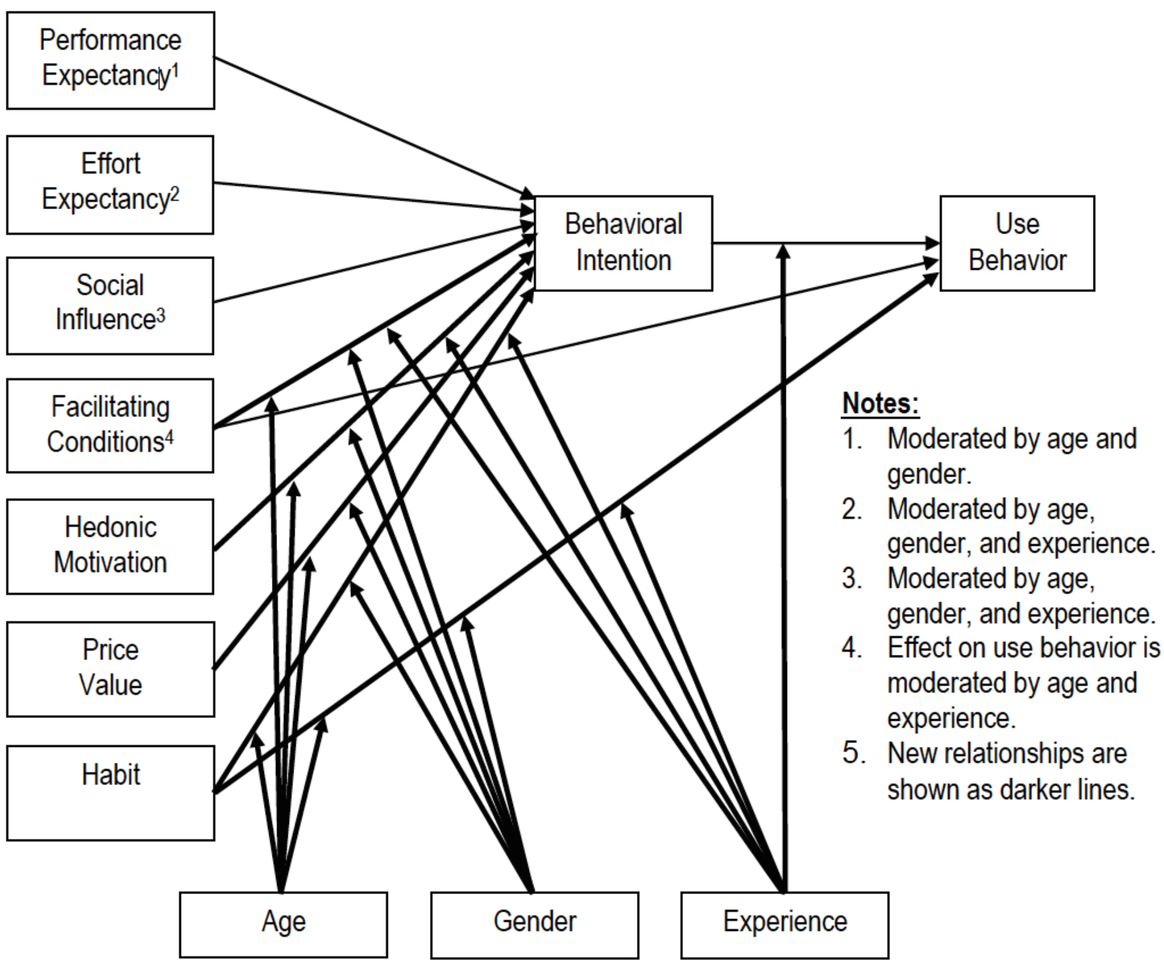
* Construct addressed in the present review

To capture factors influencing consumer acceptance of innovative technologies, Venkatesh et al. (2012) reformulated UTAUT to reflect a user-centered orientation. The extended model, UTAUT2, kept the original constructs, some of which were redefined to reflect consumer motivations, and added three more: hedonic motivation, price value, and habit. Construct definitions are provided in Table 2. In addition, voluntariness-of-use was dropped as a moderator because of its irrelevance in a consumer context; however, age, gender, and experience were retained (Figure 3). A longitudinal field study of 1,1512 mobile Internet consumers revealed that compared to the original model, UTAUT2 improved the variance explained in behavioral intention from 56% to 74% and in technology use from 40% to 52% (Venkatesh et al., 2012).

UTAUT2 in HIT research. Until recently, UTAUT2 has not been well represented in health research literature. However, in the past two years several studies have been published using this theory to gain insight into individuals' intentions to adopt HIT. For example, Tavares and Oliveira's (2016) study of 360 Portuguese clinic patients integrated UTAUT2 constructs (performance expectancy [PE], effort expectancy [EE], hedonic motivation [HM], habit, and behavioral intention [BI]) into a survey investigating contributory factors leading to the acceptance and use of electronic health records (EHR) portals. They reported that the resulting model explained approximately 49.7% of the variance in BI. Similarly, Yuan et al. (2015) found that PE, HM, price value, habit, and BI were significantly associated with 317 Midwestern college-aged students' intentions to adopt mobile health and fitness apps. They noted that even among apps used for utilitarian purposes HM significantly influenced overall technology acceptance, indicating that fun or interesting features may be key to encouraging continued use.

Apart from contributing to a clearer understanding of consumers' motivational factors for integrating emerging HIT into their daily routines, UTAUT2 has also been identified as having global policy implications. In their examination of common cross-cultural precursors to mHealth technology adoption, Dwivedi, Shareef, Simintiras, Lal, and Weerakkody (2015) surveyed citizens of the United States, Canada, and Bangladesh using UTAUT2 as the theoretical basis. Separate path analyses for each country revealed that EE, PE, price value, and social influence were similarly and significantly associated with behavioral intention to adopt new technologies. The authors suggest these findings have the potential to inform future practice for medical professionals seeking to integrate mHealth into patient care and to direct systems-level policies, especially when allocating limited resources. Moreover, they contend that by integrating a theory-based approach into the decision-making process, policy-makers are uniquely poised to improve the penetration rate of mHealth technologies within high-risk and chronically ill populations.

Figure 3. Full UTAUT2 Model



Note. Adapted from "Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology" by Venkatesh et al., 2012, *MIS Quarterly*, 36(1), p. 168.

Behavioral Outcomes

Behavioral Intention

In the UTAUT2 framework, behavioral intention bridges the gap between an individual's attitudes and actions (Venkatesh et al., 2003; Venkatesh et al., 2012). However, it is one of the least explicated concepts in the overall theory. Webb and Sheeran (2006) define an intention as a self-instruction to perform certain actions necessary to attain desired goals. Warshaw (1980) describes behavioral intention as a probability – one's subjective likelihood of performing an action. Davis, Bagozzi, and Warshaw (1989), Ajzen (1991), and (Venkatesh et al., 2003) further characterize it as a temporal function (i.e., a current decision regarding some future activity). Most of the literature in this review alludes to the meaning of behavioral intention rather than providing an outright definition.

While not always explicitly defined in technology acceptance research, intention consistently demonstrates key attributes within the context of behavioral adoption. First, it is a "mental exercise" of thinking and deciding, as opposed to overt behavioral change (Rogers, 2005). Second, it is a conscious determination of the amount of effort one is willing to expend to perform a specified future behavior (Ajzen, 1991; Warshaw & Davis, 1985). Finally, it is a discretionary decision process whereby a targeted behavior can be embraced or abandoned, meaning that user actions must be volitional to determine the strength of intention (Ajzen, 1991; Warshaw & Davis, 1985). Thus, behavioral intention can be used to estimate future consumer-level technology adoption, provided the action is voluntary (Ajzen, 1991; Arts, Frambach, & Bijmolt, 2011; Venkatesh et al., 2003; Venkatesh et al., 2012).

Behavioral intention in HIT research. Webb and Sheeran (2006) argue that correlational studies – a mainstay of behavioral health researchers – typically overstate effect sizes and ignore the possibility that an unmeasured (spurious) variable may have caused the intention or the behavior under investigation. Moreover, cross-sectional research precludes the establishment of causality. Experimental research provides the best opportunity to assess the causal pathway between intention and behavior (Webb & Sheeran, 2006). Even so, few studies empirically examine behavioral intention in any context.

In their meta-analysis examining the effects of intention on behavior, Webb and Sheeran (2006) identified 47 of 221 studies that met the criteria for experimental research. After estimating the effect sizes for different theoretical models, behavior change methods and modes of delivery, they found that a medium-to-large change in intention elicited only a small-to-medium change in behavior. While the effect was still significant, these results support assumptions that intention has a smaller impact on behavior than previously reported in correlational studies (Webb & Sheeran, 2006).

Webb and Sheeran's observations were paralleled in Or and Karsh's (2009) systematic review of consumer HIT acceptance literature. Of the 52 cited studies, six measured behavioral intention as a dependent variable (DV) using a cross-sectional design, and none investigated the relationship between intention and behavior. Focusing on mobile-specific and HIT research, this author identified nine mHealth studies that incorporated measures of behavioral intention. Four (all cross-sectional, using behavioral intention as the DV) demonstrated significant positive associations between antecedent attitudes and intention (Rai, Chen, Pye, & Baird, 2013; Ruiz-Mafé, Sanz Blas, & Fernando Tavera-Mesías, 2010; Wu, Wang, & Lin, 2007; Yuan et al., 2015). However, behavior was not directly measured, and intention could only be postulated, not confirmed, as the proxy for subsequent action.

Of the mHealth studies reviewed for this chapter, five specifically explored the intention-behavior relationship with mixed results: two randomized control studies (RCTs), one longitudinal study, and two cross-sectional studies. Tavares and Oliveira (2016) incorporated a usage measure when conducting a cross-sectional survey of 360 Portuguese clinic patients' acceptance and access of EHR portals. Using partial least squares causal modelling to analyze associations among UTAUT2 constructs and self-reported use, they found that 49.7 % of the variance in behavioral intention could be explained by specific behavioral antecedents (EE, PE, price value, and habit). However, the model could only account for 26.8% of variance in usage behavior. Lim et al.'s (2011) research, also cross sectional, attempted to assess Singaporean women's acceptance and self-reported use of mobile phones to access health information but failed to show any linkage between intention and usage. Hence, the authors opted to analyze behavioral intention as the DV in place of mobile phone use. The revised model subsequently demonstrated a significant association between antecedent attitudes and behavioral intent.

Conversely, the longitudinal study and RCTs demonstrated significant, positive associations between intention and behavior. Forquer, Christian and Tan's (2014) longitudinal research traced the evolution of 4,570 older adults' intention-to-use and actual access of an eHealth information source over a one year period. Undiminished by time, the relationship between behavioral intention and subsequent use of an eHealth newsletter remained significant. Both RCTs investigated the impact of short message service (SMS) text messaging on intent and exercise behavior among university students and among sedentary adults (Prestwich, Perugini, & Hurling, 2009, 2010). In these studies, participants randomized to the intervention arm received a series of texted motivational messages and exercise reminders over a 4-week period. Those randomized to the control arm received educational exercise materials, but not text messages.

Results indicated that the intervention positively influenced behavioral intention, which engendered small-to-moderate increases in exercise frequency and weight loss. The authors concluded that behavioral modification programs could benefit from incorporating behavioral intention into their interventions.

Although not exhaustive, this overview of HIT/mHealth literature highlights marked researcher preferences for using cross-sectional study designs to measure behavioral intention as an end-point. Yet, the inherent limitations of cross-sectional research invalidate inferences that intention acts a proxy for behavior. Additional empirical research is necessary to fully explore the magnitude of causality between intention and action in a HIT/mHealth context.

Technology Usage

If behavioral intention is conceptualized as the determination to use a technology at some future time, then usage represents the actualization of that decision. Rogers (2005) describes this as the "implementation stage," which involves the overt act of putting a new idea into practice. Unless delayed for logistical reasons (e.g., temporary unavailability of the technology), implementation typically follows the decision stage. Thus, technology usage and behavioral intention are closely tied to one another (Venkatesh et al., 2003; Venkatesh et al., 2012).

After deciding to adopt a novel innovation, consumers may still seek additional information during the implementation phase (Rogers, 2005). Arts et al. (2011) refer to this as trialability, or the "degree to which an innovation may be experimented with on a limited basis." Conceivably, trialability allays post-adoption uncertainty by allowing the individual to operate and evaluate the product; however, problems with implementation can still arise if the consumer fails to engage with the innovation. In their meta-analysis of market-based consumer adoption behaviors, Arts et al. (2011) found that high product complexity and low perceived compatibility posed significant barriers to long-term use, despite initial utilization of the technology. They concluded that trialability does not necessarily translate into permanent adoption.

Mobile technology usage. As opposed to static technologies (e.g., computers), smartphones have evolved into virtual lifestyle "Swiss Army Knives" (Böhmer, Hecht, Schöning, Krüger, & Bauer, 2011). To date, there are over 800,000 iPhone and Android software applications (apps) that are designed to assist with all aspects of daily life (McCracken, 2013). Given the sheer volume of available choices, mobile app usage represents more than technology acceptance or adoption. It delves into the mind of the consumer.

An examination of the literature reveals that consumer preferences can be extrapolated by examining variations in app installations, interaction patterns, and usage locations. Rahmati et al. (2012, 2013) reported that teenagers and low income young adults are more likely to extensively interact with recreational apps (e.g., games, social media) on their smartphones. Older adults and professionals, on the other hand, tend to access communication and productivity apps on a regular basis (Falaki et al., 2010). Böhmer et al. (2011) and Falaki et al. (2010) also found that specific app interactions tend to follow diurnal patterns. Early morning hours are peak times for accessing news and weather apps. Conversely, game play is most popular in the late evening. Finally, Do et al.'s (2011) examination of 77 European smartphone users revealed that mobile app access is largely location dependent, with the majority of usage occurring at home and at work. These findings suggest that by understanding the dynamics of consumer-to-app interactions, developers can encourage continued app usage by adapting software to align with customer needs/preferences.

Of the app studies reviewed for this chapter, all tracked usage patterns using frequencies and durations. "Frequency" refers to the number of times an app is accessed during a specified period. “Duration” refers to the amount of time, in minutes and seconds, spent using an app after it has been accessed. Böhmer et al. (2011) used frequencies and durations when examining the installation and use patterns of four thousand Android users in a four-month period. They reported aggregate usage frequencies of up to 180,000 utilizations per day and durations ranging from 40 seconds to 6.26 minutes, with average times of less than a minute. Similarly, in their research of app diversity among 255 smartphone users, Falaki et al. (2010) reported app durations of 10 – 250 seconds per interaction and frequencies ranging from 10 to 90 times per day (median of 50). Other metrics, such as data transfer and battery expenditure, are also used to track apps; however, these are not as commonly reported as the other descriptive measures.

Technology usage in HIT research. Within the body of HIT literature, post-adoption behaviors are inconsistently reported. Of the studies that do examine post-adoption usage, findings are congruent with those of marketing analyses. For example, Rho et al.'s (2014) evaluation of a diabetes intervention, a mobile-friendly electronic patient portal, revealed similar characteristics among participants who engaged in long-term implementation. Perceived compatibility – the belief that the program aligns with one’s personal lifestyle and disease self-management goals – positively corresponded with consistent technology use at four time points over twelve months.

As opposed to Rho et al.’s straightforward intervention, Carter et al.’s (2013) weight loss program, My Meal Mate (MMM), combined multiple smartphone features (mobile app, camera, and text-messaging) into a single intervention that promoted daily goal setting and food intake monitoring, including a pictorial food diary using the camera function. This three-armed pilot randomized trial examined the feasibility and acceptability of the MMM app compared to a self-monitoring website and a food diary. One hundred and twenty-eight individuals were recruited for the study, with approximately 43 participants per group. The primary outcome measure was frequency of use; secondary measures were objectively obtained anthropometrics. Over the 6-month study period, the authors reported that frequency-of-use was the highest in the MMM group with a mean of 92 total days the app was accessed (note: results were reported as aggregate data rather than individual use). In comparison, the diary group and website group completed 29 and 35 days, respectively. Because of the high attrition rate in the website (n=23) and diary (n=23) groups, the study was not sufficiently powered to detect significant anthropometric changes at 6 months. Although the attrition rate was high in the comparison groups, the authors reported low attrition (n=3) in the MMM group. Among those who failed to complete the MMM arm of the program, the most common reason for dropping out was a dislike of the study equipment (smartphone and app). While the term "dislike" was not fully explicated, the complexity of the intervention may have a produced an operational barrier. However, the extent to which these participants encountered difficulties using the smartphone and app remains unknown.

Behavioral Intention Antecedents

Performance Expectancy

In the original UTAUT model, performance expectancy was described as a set of beliefs regarding a technology's likelihood of enhancing work performance and job advancement (Davis, 1989; Venkatesh et al., 2003). Later, Venkatesh et al. (2012) redefined performance expectancy to reflect the consumer's perspective in UTAUT2: "the degree to which using a technology will provide benefits to consumers in performing certain activities." An antecedent to behavioral intention, performance expectancy influences intention through extrinsic mechanisms which motivate behavior by reinforcing the value of outcomes (Davis, Bagozzi, & Warshaw, 1992; Venkatesh et al., 2003). Derived in part from "relative advantage" (DOI) and "perceived usefulness" (TAM) – see Table 1 – performance expectancy is tied to an internal cost-benefit analysis, in which the relative advantages of a behavioral change are weighed against its relative disadvantages (Davis, 1989; Rogers, 2005). As such, it is one of the strongest predictors of intention in both voluntary and mandatory settings (Venkatesh et al., 2003).

Performance expectancy in HIT research. Within the body of HIT acceptance literature, performance expectancy has been shown to consistently influence behavioral intention over time. In their pre- and post-use examination of physicians' acceptance of a speech recognition dictation system, Alapetite et al. (2009) found that performance expectancy was moderately associated with behavioral intention prior to using the new technology. Four months after the dictation system was implemented, the physicians were re-surveyed. Results indicated that performance expectancy remained unchanged and undiminished by technology usage. Venkatesh et al.'s (2011) longitudinal study of physicians' EHR adoption reported similar findings: performance expectancy remained consistent and significantly associated with behavioral intention over the course of seven months. Several other studies, mainly cross-sectional, have also demonstrated significant associations between performance expectancy and behavioral intention, especially when providers perceived the targeted technology as job-enhancing: Yi, Jackson, Park, and Probst's (2006) examination of physicians' acceptance of a PDA-based decision support tool; Duyck et al.'s (2010) survey of radiologists' willingness to adopt a digitized picture archiving system; and Chang et al.'s (2007) evaluation of Chinese physicians' intention to use a pharmacokinetics-based clinical decision support system.

While a large portion of HIT research centers on health care providers' perceptions, a growing number of studies indicate that within the context of technology acceptance, performance expectancy significantly influences patients' intention and adoption behaviors. For example, in Preusse, Mitzner, Fausset, and Rogers' (2016) 28-day field trial assessing older adults' (n=16, aged 65-75 years) acceptance of an activity tracking device and a free website (FitBit One, Myfitnesspal.com), usage attitudes and behaviors were evaluated by surveys and qualitative interviews. During the final interview, participants who articulated the relative benefits of using these technologies (e.g., step goals, tracking food intake) were more likely to state they would continue using the product websites and tracking devices even after completing the study. Similarly, in a 7-month long study of heart failure patients' acceptance and use of a web-based eHealth intervention, Or et al. (2011) reported that perceived usefulness accounted for approximately 54% of variance explaining behavioral intention to access and subsequently use the website. Emani et al.'s (2012) survey of 760 clinic-based patients also revealed that relative advantage drove intentions to adopt or reject the use of personal health records (PHR) as a self-management tool. In all studies, patients were more open to adopting HIT when they perceived the usefulness of the targeted technology to directly benefit their health. These results imply that across the health care continuum, both providers and patients are equally vested in reaping the advantages of newly introduced HITs.

Effort Expectancy

Effort expectancy is defined as "the degree of ease associated with the use of technology" (Venkatesh et al., 2003, 2012). Framed in terms of personal judgment, effort expectancy encompasses beliefs regarding perceived system complexity and the difficulty involved operating a technology (Venkatesh et al., 2003). Hence, if a technology is deemed difficult or complex, individuals are less likely to use it (Venkatesh et al., 2003, 2012). Those who are most influenced by effort expectancy are older individuals, women, and the technology-inexperienced (Venkatesh et al., 2003).

Effort expectancy in HIT research. Like performance expectancy, effort expectancy exerts significant motivational influences on behavioral intention (Venkatesh et al., 2003, 2012). Among HIT acceptance studies, effort expectancy/ease-of-use has been associated with increased satisfaction among diabetic patients' use of a telemedicine intervention (Rho et al., 2014), HIV patients' willingness to utilize mHealth programs to improve medication adherence (Baranoski et al., 2014), and health care professionals' acceptance and adoption of innovative HIT systems (Gagnon et al., 2012). Conversely, difficulties interacting with a new technology present significant operational barriers blocking eventual acceptance and adoption. In their qualitative examination of older adults' acceptance of popular fitness trackers (e.g., MyFitnessPal, Fitbit), Preusse et al. (2016) noted that non-intuitive formats coupled with difficulties entering data into food diaries were among the most cited reasons for disliking the trackers. Most of these were usability issues associated with participants not understanding how the trackers worked or not knowing how to use the corresponding software interfaces. Participants who complained of these problems did not want to spend extra time learning to use a new technology that made no inherent sense to them. Subsequently, they used the trackers less or not at all.

Although effort expectancy has been shown to be an important precursor to behavioral intention, it becomes a less influential factor under certain conditions. Consistent with Venkatesh et al.'s (2003) observations, both gender and technology expertise moderate the association between effort expectancy and behavioral intention. Hamid and Cline (2013) and Venkatesh and Morris (2000) found that, as opposed to women, perceived ease-of-use was a less significant consideration among men when contemplating adopting novel technologies. Similarly, Or et al. (2011) and Sicotte, Taylor, and Tamblyn (2013) reported that the effects of effort expectancy, or ease-of-use, on behavioral intention was inversely related to degree of experience using the targeted technology. Technologically experienced persons were less likely to be motivated by ease-of-operation. Or et al. (2011) speculated that these associations might be temporally related (e.g., the amount of time elapsed between teaching someone to use a system and giving them a survey); however, additional research is needed to explore the effects of time and experience on effort expectancy.

Hedonic Motivation

Hedonic motivation, “the fun or pleasure derived from using a technology,” focuses on the innate amusement afforded to the user (Venkatesh et al., 2012). An antecedent to behavioral intention, hedonism influences intention through intrinsic pathways (Davis et al., 1992). In other words, one performs an activity from the hedonic perspective “for the fun of it” and in the absence of palpable gain (Davis et al., 1992; Venkatesh et al., 2012).

In a marketing context, hedonic motivation significantly influences individuals’ purchase/usage intentions (Brown & Venkatesh, 2005; Childers et al., 2001). Dickinger et al. (2008) and Van der Heijden (2004) note that, in the case of innovation, hedonic motivations are often the strongest determinants of intention, even superseding perceived usefulness. Childers et al. (2001) point out that hedonic motivations are often contextual. When the technology is novel or “fun,” hedonic considerations take primacy over other motivations; otherwise, consumers strike a balance between utilitarianism (practicality) and hedonism during the decision-making process. Brown and Venkatesh (2005) further conceptualize hedonic motivation as a temporal construct that diminishes over time. For example, younger consumers typically place more importance on fun seeking than do their older counterparts.

Hedonic motivation in HIT research. Within an HIT context, the concept of hedonic motivation has received little attention. Of the studies reviewed for this chapter, only one integrated hedonic motivation into its theoretical framework. Forquer et al. (2014) examined the long-term use of an eHealth newsletter among 4,570 older adults participating in a yearlong nationwide study. Results did not support the hypothesis that hedonic motivation would become more positively associated with intention over time. Instead, the opposite occurred – hedonic motivations and intention weakened over time. Like Childers et al.'s observations, the authors speculated that as the newsletter's novelty wore off, so did continued interest.

Moderating Influences

EHealth Literacy

Understanding that certain foundational skills are necessary for HIT use, Norman and Skinner (2006a, 2011) reframed the concept of health literacy to become a type of "meta-literacy" that subsumes six distinct domains (Table 3): traditional literacy, information literacy, media literacy, health literacy, computer literacy, and scientific literacy. The new concept, eHealth literacy, is thusly defined as "the ability to seek, find, understand, and appraise health information from electronic sources and apply the knowledge gained to addressing or solving a health problem" (Norman & Skinner, 2006a). Within this context, eHealth literacy is conceptualized in terms of action because it involves proactive behaviors (e.g., accessing IT, researching/evaluating health information) and problem-solving skills (Institute of Medicine [IOM], 2009). Consequently, it is a dynamic process that can improve with experience over time; however, without sufficient abilities *across* these literacy domains, individuals are unlikely to take advantage of eHealth resources (Norman & Skinner, 2006a).

EHealth Literacy in HIT research. In a workshop examining long-term implications of transitioning to an IT-driven health system, the IOM (2009) cautioned that without adequate

Table 3
Domains contained within eHealth literacy

Domain	Definition
Traditional literacy	"Prose" literacy – reading and numeracy
Information literacy	Knowing how information is organized, located, and applied
Media literacy	Ability to critically appraise media content
Health literacy	Ability to read, comprehend, and act on health information
Computer literacy	Ability to use computers for problem-solving
Scientific literacy	Understanding the natural, sociological, and political aspects of science

eHealth literacy, worsening health disparities could arise within disadvantaged and underserved populations. Among those at risk are the elderly (Choi & Dinitto, 2013; Hall, Bernhardt, Dodd, & Vollrath, 2014), minorities (IOM, 2009; Neter & Brainin, 2012), non-English-speaking immigrants (IOM, 2009), low income wage earners (E. Kontos, Blake, Chou, & Prestin, 2014; Neter & Brainin, 2012), poorly educated (Jensen, King, Davis, & Guntzviller, 2010; Neter & Brainin, 2012) and male gender (Jensen et al., 2010; E. Kontos et al., 2014). Interestingly, female gender is associated with higher overall eHealth utilization (Jensen et al., 2010; E. Kontos et al., 2014; Percheski & Hargittai, 2011).

Of individuals who fall into the above risk groups, chronically ill and cognitively impaired persons are particularly susceptible to poor health management through the ineffective utilization of eHealth (Neter & Brainin, 2012). One survey of 324 HIV-infected adults revealed that respondents tended to assign similar credibility to websites promoting unproven, even sensational, HIV management strategies compared to those sites that offer medically sound advice (Benotsch, Kalichman, & Weinhardt, 2004). The authors ascribed this lack of critical appraisal to educational/economic disadvantage and the belief that Internet information sources are usually dependable. In a separate study, Sarkar et al. (2010) also discovered that technology availability does not guarantee effective technology use. Among clinic-based diabetics with a reliable means of accessing the Internet, patients with low literacy levels (reading/numeracy) were generally less likely to use all components of an Internet Patient Portal – registering, signing on, making appointments, requesting refills, viewing labs, and emailing healthcare providers – than their more literate counterparts. Connolly and Crosby (2014) discussed similar issues during focus group sessions with low-income Hawaiian diabetics suffering poorly controlled disease. Lacking sufficient resources and technical abilities to operate a computer/smartphone beyond basic functions, many of the participants (mean age 54 years) reported an inability to retrieve or use Internet-based health information despite a desire to do so. Many had to rely on technically savvy younger family members to assist with more complex device operations and/or search functions. The ramifications of these observations, when viewed through the lens of eHealth literacy, are twofold: 1) eHealth tools/information are neither equitably distributed nor are they universally accessible, and 2) the quality and frequency of actual HIT use can be largely dependent on third-party eHealth literacy (e.g., family members). Thus, these patients face potential operational barriers stemming poor access and inadequate skill levels, both theirs and their family members.

Future eHealth literacy studies should investigate its impact on motivational elements within a technology acceptance framework. Although associations between poor eHealth literacy and low HIT adoption are strong, the mechanisms by which eHealth literacy affects technology acceptance remain unexplored. Research results could be especially salient when evaluating whether low eHealth literacy impedes behavioral intention among individuals who are technology-resistant. A better understanding of these relationships could inform the development of more effective HIT interventions.

Experience

In a technology adoption framework, experience is a multifaceted concept suggestive of an underlying familiarity with and exposure to using a targeted technology (Dishaw & Strong, 1999; Sun & Zhang, 2006). Venkatesh et al. (2012) define experience as an opportunity to operate a technology. Varma and Marler (2013) further describe it as a level of technology knowledge and competency. In all cases, experience is framed as a temporal process that is operationalized as time spent using a technology from the point of initial exposure (Sun & Zhang, 2006; Varma & Marler, 2013; Venkatesh et al., 2012).

In the UTAUT2 model, experience acts as a modifying variable that influences both antecedent-to-intention and intention-to-behavior relationships (Figure 3). Habit, on the other hand, directly affects behavioral intention as an antecedent influence. Since they both focus on usage behaviors, habit and experience are closely linked, and the distinction between the two can become muddied. Experience differs from habit in two respects: 1) habit encompasses experience, but experience itself is not a sufficient condition to form habit, and 2) over time, habit becomes an automatic response resulting in routine (normative) behavior, while experience does not necessarily imply customary use (Varma & Marler, 2013; Venkatesh et al., 2012).

Marketing research consistently demonstrates the moderating effects of experience on behavioral constructs within technology acceptance frameworks (Sun & Zhang, 2006; Venkatesh et al., 2003; Venkatesh et al., 2012). Rationales in support of these findings center on increased self-efficacy, enabling users to try new technologies after positive experiences using a similar one (Porter & Donthu, 2006). In addition, technology experience has been associated with higher perceived ease-of-use and more effortless adaptation to new technologies (Sun & Zhang, 2006; Venkatesh et al., 2003; Venkatesh et al., 2012; Weinberg, 2004).

Experience in HIT research. In HIT adoption literature, the moderating influence of experience on technology acceptance has not been widely examined. Studies that have measured experience as a variable typically focused on provider adoption of technology, such as EHR. Research findings in these studies are like those of marketing studies. For instance, Li et al.'s (2013) systematic review of provider adoption of eHealth revealed that previous exposure to IT technology influenced physician acceptance of new HIT. If the experience was positive, the physician was more likely to adopt a novel technology; however, negative experiences adversely affected behavioral intention and subsequent adoption. Nonetheless, Venkatesh et al.'s (2011) examination of physician's acceptance of EHR systems revealed that experience did not moderate relationships within the UTAUT framework. The authors found that with greater experience, transitioning to a new, but similar, IT system is perceived as less disruptive. As experience approaches habit, the dynamics of its moderating relationship with the overall model become less significant.

As opposed to its influence on technology acceptance among health care providers, the impact of experience on consumer HIT adoption is unclear. Of the literature reviewed for this chapter, none addressed the moderating effects of experience on consumer adoption within a technology acceptance framework. Because many patients/consumers have had at least some exposure to information technology (e.g., computers, smartphones), the degree to which experience moderates attitudes towards adopting innovative health technologies into a health management routine should be more fully explored.

Conclusion

The literature review presented in this chapter highlights the scarcity of studies examining the components of sustainable patient-oriented HIT interventions, especially mHealth apps. Despite the growing need for convenient and innovative technology-based treatment adjuncts, patient uptake remains disproportionately low (Krebs & Duncan, 2015; Samhan et al., 2013). Current research sheds little or no light on the reasons behind the mismatch between mHealth app development and patient usage, especially since few mHealth or HIT interventions in this review appear to have been developed with an underpinning theoretical framework. Consequently, there is insufficient theoretical insight into critical factors motivating long-term patient acceptance and adoption of novel technology-based treatment approaches.

Of existing technology acceptance theories, UTAUT2 is uniquely positioned to evaluate mHealth technology acceptance and adoption from a consumer (i.e., patient) perspective. Unlike the original UTAUT model, which focuses on organizational factors motivating technology adoption, UTAUT2 recognizes that individuals' motivations for accepting new technologies are embedded in their innate perceptions of technology-associated personal gain, operational ease, and enjoyment. Ideally, these perceptions positively increase the behavioral intention to use a technology, which then activates real usage.

Though not extensive, a growing body of literature supports the assumption that UTAUT2 captures the associations between behavioral intention and its antecedent conditions. Research suggests that these relationships can shed light on the fundamental facilitators and barriers affecting technology adoption within target groups. Nonetheless, the linkage between behavioral intent and the act of HIT or mHealth adoption remains ill-defined, with few studies examining real-time use from a theoretical standpoint. Similarly, the impact of both eHealth literacy and baseline technology experience on the relationship between behavioral intent and its theoretical antecedents is largely unexplored.

The present study sought to examine theoretical factors motivating individuals' adoption of a smartphone-based intervention through the lens of UTAUT2. It also evaluated the association between behavioral intention and real-time iApp usage. In addition, the effects of eHealth literacy and technology experience on mHealth acceptance were examined. Results of this research can be used to inform the future development of sustainable mHealth apps.

CHAPTER 3

METHODS

This chapter presents the methods that were used to answer the proposed research questions and test the related hypotheses. Study specifics are presented in the following sections: overview, setting, study sample, procedure, research instruments, data management, and data analysis.

Overview

This study employed a theory-based approach to evaluate factors associated with the adoption of the MFHP's iApp, which was designed to enhance HIV disease self-management. Three questions drove this research. First, do behavioral intent antecedents influence behavioral intent to use the iApp? Second, does behavioral intent determine the actual use of the iApp? Finally, do eHealth literacy and smartphone experience moderate the relationship between behavioral intent antecedents and behavioral intent?

To answer these research questions, participant acceptance and usage of the iApp were evaluated. Because this research was contained within MFHP parent study, all the proposed study-related activities were contingent upon the MFHP's existing policies and procedures. Moreover, research participants for this study must have been enrolled in the intervention arm of the main study. The following section will furnish a more detailed description of the MFHP.

Music for Health Project

The MFHP is an NIH/NINR-funded RCT conducted by Marcia McDonnell Holstad, PhD, of Emory University's Nell Hodgson Woodruff School of Nursing. The purpose of this research is to evaluate the efficacy of an mHealth app to promote ART adherence and symptom self-management for persons living with HIV/AIDS (PLWHA) who reside in rural Georgia.

PLWHA living in rural circumstances risk adverse health outcomes and early death related to inadequate disease self-management, disadvantaged socioeconomic status and barriers accessing health care (Hormes & Theall, 2013; Konkle-Parker, Erlen, & Dubbert, 2008). Therefore, these individuals stand to gain substantial health benefits from using mHealth programs that motivate and enable effective self-management behaviors.

To be included in the MFHP, participants must be: 1) HIV-positive; 2) at least 18 years old; 3) English-speaking; 4) willing to be randomly assigned to the educational or intervention study arm, take part in study-related activities and use a smartphone; and 5) ART naïve, starting a new ART regimen within the past 12 weeks, or have a detectable viral load while on ART between 3 months and a year. Individuals are excluded from the study if they have self-identified bilateral hearing loss, cognitive impairment or severely depressive/suicidal symptoms.

Those who meet the MFHP's eligibility criteria are randomized to one of two study arms: 1) the intervention arm using the iApp, or 2) the control arm using the educational app (eApp). The iApp consists of a music-based simulated "talk radio" program, an interactive HIV resource manual with active web links, and animated videos based on the music portion of the app. Specifically developed for this study, the iApp covers topics previously identified by Holstad, Ofotokun, Higgins, and Logwood (2013) as important motivators of self-care among PLWHA. These include medication adherence strategies, self-efficacy, symptom self-management, disclosure advice, goal setting, and managing depression. The eApp also contains music, a resource manual with active web links, and content-related videos; however, none are health-related. Educational topics include important American historical figures/events, finance/debt information, how to rent an apartment, census information, principles of childcare, and pet care tips. Both the iApp and eApp contain a survey link to answer questions about medication-taking behaviors and to conduct pill counts.

The appropriate app for each group (iApp versus eApp) comes preloaded onto Verizon Wireless Code Division Multiple Access (CDMA) 3G network-capable Motorola DROID RAZR M smartphones that are given to study participants for the 9-month study. App usage is voluntary, with participants deciding the frequency and duration of their app-related interactions. Regular text-message reminders to use the app are sent by MFHP staff on a predetermined schedule. Monthly outcome measures – in-app surveys and pill counts – are required. Other outcome measures include hair samples for ART levels, medical record abstractions for lab data, and computer-based behavioral surveys conducted every three months.

Setting

Research activities were conducted at Georgia Department of Public Health (GDPH) clinics in the following rural counties (cities): Bibb (Macon), Clarke (Athens), Glynn (Brunswick), Muscogee (Columbus), and Richmond (Augusta). All are part of the Ryan White Part B program, which provides uninsured or underinsured PLWHA access to core medical services: AIDS Drug Assistance Program, outpatient/ambulatory health, oral health, outpatient substance abuse care, and mental health counseling (GDPH, 2012). To receive Ryan White Part B services in Georgia, a client must be a Georgia resident 18 years of age or older; diagnosed with HIV or AIDS; not covered by or eligible for Medicaid or another third party payer; have cash assets equal to or less than $4500; and earn an income below 300% of the Federal Poverty Level (GDPH, n.d.).

Study Sample

Recruitment took place at the participating GDPH clinics. Aside from the eligibility conditions previously outlined for entrance into the MFHP, the primary inclusion criterion for this research was randomization into the intervention arm of the parent study. Individuals allocated to the education arm of the study were excluded.

Projected Sample Size

The projected recruitment rate for the MFHP was 15 persons per month from all five sites; therefore, it was anticipated that 180 people would enter the study in a one-year timeframe. Using Holstad et al.'s (2013) previous music-based research as a guide, a sample size of 149 was calculated using an attrition rate of 17%. However, this sub-study only focused on the intervention subjects, which was expected to yield a sample size of 75 subjects. For the three aims stated above, all of which were to have involved multivariate regression of one to three variables tested after controlling for one to two covariates, moderate effect sizes were expected for Δr^2 (change in r-squared) of 0.13 for a sample size of 75 at 80% power and 5% level of significance. Power analyses were completed using PASS, Version 13 (Hintze, 2014).

Actual Sample Size

Between March 2015 and February 2016, 34 participants were randomized into the intervention arm of the MFHP. Recruitment rates were inconsistent across all sites despite active screening efforts by study personnel and clinic liaisons, with some going weeks with few or no new participants. Factors contributing to the low recruitment rate are detailed in Chapter 5.

Because the sample size was less than half of the expected 75 participants and data results had limited variability, adjustments were made to the initial statistical analysis plan. Specifically, hypothesis testing was conducted using nonparametric statistics, as opposed to the originally planned parametric tests. The Statistical Analysis section of this chapter gives a more thorough accounting of which tests were employed.

Procedure

Recruitment

Prior to commencing this research, approval by the Institutional Review Boards (IRB) of Emory University was obtained by Dr. Holstad to add this sub-study's instruments to the baseline and 3-month follow-up assessments of the MFHP study. After IRB approval, data from those participants randomized to the MFHP iApp between March 2015 and February 2016 were used for this project. As noted above, 75 participants were anticipated but only 34 were recruited. Although the MFHP's duration is 9 months, this research focused on each participant's first 3 months (100 days) in the program. Table 4 presents an overview of key measures used for this study.

Participants were recruited for the MFHP parent study using three approaches: 1) study flyers displayed at each MFHP study site; 2) self-referrals by interested persons who call the study office or directly approach a local site coordinator; and 3) referrals from healthcare providers. In addition, local MFHP site coordinators worked with key contacts for further assistance. Key contacts are highly placed professionals (e.g., nursing supervisors, case managers) within each clinic who act as initial liaisons between potential recruits and research staff. These individuals were trained by the MFHP program coordinator to identify eligible patients and to distribute study-related information, such as recruitment brochures. Key contacts either directly referred interested persons to the local site coordinator or provided lists of eligible patients for follow-up and screening.

Table 4

Main measures, delivery method, and timeline

Variable	Measure/Instrument	Delivery Mode	Baseline	3 Months	Daily
Independent Variables (Smartphone acceptance)					
Performance Expectancy (PE)	UTAUT2 PE subscale	ACASI	X	X	
Effort Expectancy (EE)	UTAUT2 EE subscale	ACASI	X	X	
Hedonic Motivation (HE)	UTAUT2 HM subscale	ACASI	X	X	
Behavioral Intention (BI)	UTAUT2 BI subscale	ACASI	X	X	
Moderators					
eHealth Literacy	eHEALS	ACASI	X	X	
Smartphone experience (SPexp)	SPexp survey	ACASI	X		
Outcomes					
Frequency iApp use	Number of app openings	Flurry Analytics			X
Duration iApp use	Minutes spent in app	Flurry Analytics			X

Screening, Baseline and Follow-up

Site coordinators interviewed recruits to verify basic eligibility for inclusion in the MFHP parent study and to screen for exclusion criteria – severe depression and/or cognitive impairment. Those with severe depression were referred to a mental health specialist for further evaluation and were eligible for rescreening after receiving clearance from this specialist. (None of the iApp participants in this sample required a mental health referral.) Once eligibility was confirmed, each participant signed a consent form and commenced the baseline surveys via audio computer-assisted self-interview software (ACASI). ACASI is a survey method frequently used in clinical research settings to capture sensitive patient information, such as high-risk or stigmatizing behaviors. As compared to standard paper-and-pencil surveys, screening information collected using ACASI may yield more complete data, possibly due to better privacy controls (Estes et al., 2010; Pluhar et al., 2007; Reichmann et al., 2010).

After completing the baseline surveys, participants were randomized per MFHP protocol to the iApp or eApp arm of the study. As stated in the MFHP protocol, once randomized, the participant received a smartphone with the appropriate app preloaded onto the device. The site coordinator focused subsequent educational activities on smartphone operation, including how to access and use the study app. Teaching techniques were interactive, with demonstrations (coordinator) and return demonstrations (participant).

Per MFHP protocol, all participants were scheduled for study follow-up assessments at 3, 6, and 9 months post-baseline. In addition to the standard MFHP questionnaires, the baseline and 3 month ACASI assessments contained the surveys noted in Table 4. Continuous app usage data were captured using Flurry Analytics for all MFHP over the 9-month study period. This study used data from the instruments in Table 4 for those randomized to the iApp condition and Flurry data for the iApp usage between the baseline interview and the 3-month follow-up for participants enrolled between March 2015 and May 2016.

Research Instruments

The following description of study measures is organized by variable-type. The main independent variable was iApp acceptance, encompassing effort expectancy, performance expectancy, social influence, and behavioral intention. Moderating variables were eHealth literacy and previous smartphone exposure. The main dependent variable was real-time iApp usage. Permissions have been obtained from Dr. Venkatesh and from Dr. Norman to use their respective surveys, UTAUT2 and eHEALS (Appendixes A-B). Permission by Dr. Venkatesh to modify the UTAUT2 scale was also obtained (Appendix C).

Independent Variable: iApp Acceptance

Modified UTAUT2 survey. Venkatesh et al.'s (2012) UTAUT2 survey subscales were used to measure antecedents (performance expectancy, effort expectancy, hedonic motivation) and behavioral intent to use the MFHP smartphone intervention (Appendix D). This instrument was originally developed to measure constructs related to mobile Internet acceptance and use. For this study, the survey was modified to reflect smartphone app acceptance and use; therefore, the term 'mobile Internet' was substituted by 'smartphone app' to reflect the targeted technology. The Flesch-Kincaid grade level for the combined revised subscales is 4.6.

Items were scored using a 7-point Likert scale, from 1 (strongly disagree) to 7 (strongly agree). With all subscales combined, survey totals can range between 14 and 112. Higher scores indicate greater acceptance and intent to adopt the target technology.

Performance expectancy. The 4-item performance expectancy subscale measures the perceived benefits that a technology can afford to the consumer. A representative statement is, "I find mobile Internet (smartphone apps) useful in my daily life." Wording was changed in the last statement of this subscale from, "Using mobile Internet increases my productivity," to, "Using a smartphone app will help me stay healthy." The rationale for this change is that health is an important goal for the population in question.

Scores range from 4 to 28, with higher totals indicating better perceptions of technology-related benefits. Venkatesh et al. (2012) reported good internal consistency reliability (ICR) for this subscale, with a Cronbach's $\alpha = 0.88$.

Effort expectancy. The 4-item effort expectancy subscale measures the ease with the consumer can learn and operate the targeted technology. A representative statement from section is, "I find mobile Internet (smartphone apps) easy to use." Wording was changed in the second item from, "My interaction with mobile Internet is clear and understandable," to, "Smartphone apps are clear and user-friendly to use." The rationale behind this revision is that all survey respondents may not easily understand the wording of the first statement. Per the Flesch Reading Ease test, the original statement was worded at twelfth-grade reading level. The revised version was worded at a fifth-grade level.

Scores range from 4 to 28, with higher totals indicating greater beliefs that the technology is easy and accessible. This subscale demonstrated an excellent ICR, with a Cronbach's $\alpha = 0.91$ (Venkatesh et al., 2012).

Hedonic motivation. The 3-item hedonic motivation subscale is measures the pleasure, or enjoyment, the consumer experiences from using a technology. A representative statement from this section is, "Using mobile Internet (a smartphone app) is fun." Scores range from 3 to 21, with higher totals indicating that the technology is more fun to use. Psychometric evaluation indicates good ICR, with a Cronbach's $\alpha = 0.88$ (Venkatesh et al., 2012).

Behavioral intent. The 3-item behavioral intent subscale measures the decision to engage in future action, such as adopting a new technology. Wording in the second item was changed from, "I will always try to use mobile Internet in my daily life," to, "I will always try to use a smartphone app to track my health." The change in wording reflects a better alignment with the goals of the present study.

Scores range from 3 to 21, with higher totals indicated a greater intent to use or adopt the technology. This subscale demonstrated an excellent ICR, with a Cronbach's $\alpha = 0.93$ (Venkatesh et al., 2012).

Moderators: eHealth Literacy and Smartphone Experience

eHealth Literacy Scale (eHEALS). eHEALS is a self-evaluation of perceived skills at finding and using electronic health information (Norman & Skinner, 2006b). Norman and Skinner (2006a) describe eHealth literacy as a complex, multidimensional construct that spans traditional, health, information, scientific, media, and computer literacies. From a clinical standpoint, the eHEALS has been envisioned as the first step in determining the appropriateness of prescribing an eHealth intervention, such as directing a patient to online resources (Collins, Currie, Bakken, Vawdrey, & Stone, 2012).

Derived from self-efficacy theory, eHEALS is an 8-statement survey that measures an individual's self-confidence and beliefs regarding his or her ability to locate and manage health resources on the Internet (Norman & Skinner, 2006b). Later, the survey was expanded to include two additional statements about the importance and usefulness of eHealth information; however, these are not scored as part of eHEALS (Norman, 2011). Each item is rated on a 5-point Likert Scale, where 1 = Strongly disagree, 2 = Disagree, 3 = Undecided, 4 = Agree, and 5 = Strongly agree (Appendix E). Higher scores indicate better eHealth literacy. Psychometric evaluation revealed a good ICR, with a Cronbach's $\alpha = 0.88$, and modest test-retest stability over 6 months (Norman & Skinner, 2006b).

Smartphone Experience Questionnaire (SPexp). Smartphone experience was evaluated once at baseline with a 14-item questionnaire devised to assess participants' pre-study exposure to using smartphones and mobile information technologies (Appendix F). This measure was adapted from the *Substance Abuse Questionnaire* (SAQ), used in the MFHP parent study, and which is used to estimate the number of times participants have engaged in substance use over the past three months. Permission was received from Dr. Holstad to use the SAQ as a template for the SPexp.

The first 4 questions of the SPexp focus on smartphone ownership and use. Representative questions are, "Have you ever owned a smartphone?" and "Have you had any experience using a smartphone?" Responses to these questions are "Yes," "No," or "Don't know." If the respondent has either owned or used a smartphone, he or she is asked to specify the duration of exposure in terms of time (e.g. weeks, months, or years). The questionnaire ends at the fourth item if the participant has never had experience using a smartphone.

The next 10 questions ask about mobile activities performed on a smartphone in the past three months: emails, SMS, multimedia messaging service (MMS), camera/video functions, mobile media (music and video), app use, and Internet access**.** A sample question is as follows: "In the past three months, how often have you used a smartphone to… send or receive emails?" Each item is rated on a 5-point Likert scale, where 1 = Never, 2 = Less than once a week, 3 = 1-2 days a week, 4 = 3-6 days a week, and 5 = Every day. Scores range from 10 to 50, with higher totals indicating greater smartphone experience. Reliability testing, which was performed using this study's sample, indicated high internal consistency, with a Cronbach's alpha of .971.

Dependent Variable: Real-time App Usage

In the parent study, real-time MFHP app usage was assessed using benchmark tools from Flurry Analytics (n.d.), a Yahoo-owned analytics firm that specializes in tracking and researching consumer interactions with mobile apps and advertising. By enabling the tracking function on each participant's smartphone, the following metrics were remotely collected using the Flurry platform: event-type (i.e., music, manual, video), session index (i.e., individual song, video, or manual chapter), and time/frequency parameters (times logged in and out; total time spent in the app) for the duration of the parent study. For this study, each participant's frequency of access (the number of times the app was opened) and duration (the number of seconds spent in the app) was captured between baseline and 3 months. Usage was examined broadly (overall app frequency/duration) and narrowly (frequency/duration by event-type). Session indexes were not evaluated.

Data Management

The MFHP used Research Electronic Data Capture (REDCap) to collect and provide encrypted storage for MFHP's demographic and other study information. REDCap is a secure, web-based application designed to support data capture for research studies, providing 1) an interface for validated data entry; 2) audit trails for tracking data manipulation and export procedures; 3) automated export procedures for data downloads to common statistical packages; and 4) procedures for importing data from external sources (Harris et al., 2009).

ACASI-based behavioral surveys (including those used for this study) were conducted by MFHP study staff on password-protected laptop computers and uploaded to the secure Questionnaire Development System (QDS) data warehouse. Real-time smartphone usage was stored in Flurry Analytics' secure, password-protected database. Data from REDCap (demographics), QDS (modified UTAUT2, eHEALS, and SPexp) and Flurry Analytics (iApp use) for the 34 iApp participants were downloaded from the MFHP's encrypted database for analysis. These data were stored separately on a secure, password protected server. In addition, a formal data agreement was signed by Dr. Holstad and myself to ensure all data are properly handled.

Data Analysis

This section discusses the statistical approaches used to test the hypotheses for this observational study (Figure 4). A recap of research questions and related hypotheses is as follows:

Question 1. Are performance expectancy, effort expectancy, and hedonic motivation associated with behavioral intent to use the MFHP iApp?

H1-A: Performance expectancy has a direct positive association with behavioral intent to use the iApp.

H1-B: Effort expectancy has direct positive association with behavioral intent to use the iApp.

H1-C: Hedonic motivation has a direct positive association with behavioral intent to use the iApp.

Question 2: Is behavioral intent associated with the number of times the MFHP iApp is accessed?

H2: Behavioral intent will be positively associated with the number of times iApp is accessed. Increased behavioral intent to use the iApp will result in a higher frequency of MFHP access.

Question 3: Is behavioral intent associated with the amount of time spent using the MFHP iApp?

H3: Behavioral intent will be positively associated with the amount of time spent using the iApp. Increased behavioral intent to use the iApp will result in a longer duration of time spent using MFHP app.

Question 4: Do eHealth literacy and smartphone experience moderate the relationship between behavioral intent antecedents (performance expectancy, effort expectancy, and perceived enjoyment) and behavioral intent?

H4-A: eHealth literacy moderates the association between behavioral intent antecedents and behavioral intention. The association with behavioral intent will be diminished in the presence of low eHealth literacy.

H4-B: Smartphone experience moderates the association between behavioral intent antecedents and behavioral intention. Smartphone inexperience will weaken the association between the antecedents and behavioral intent.

Statistical Analyses

Both descriptive and inferential statistical approaches were employed to analyze data. Descriptive statistics summarized demographic characteristics, survey results, and outcomes. These included frequencies, percentiles, measures of central tendency, and standard scores. Inferential statistics were used for hypothesis testing, with analyses performed at the 5% significance level ($\alpha = .05$). All procedures were conducted using SPSS Statistics for Macintosh, Version 22 (IBM Corp., 2013).

Preliminary analysis. Prior to hypothesis testing, data were transformed to preserve data points and facilitate statistical analysis. Categorical demographic variables were dichotomized by gender (male versus female), sexual identity (heterosexual versus homosexual/bisexual), race (African American/black versus all other races), marital status (relationship versus no relationship), educational status (high school versus post-high school), living arrangement (living alone versus living with others), employment (employed versus unemployed) and current smartphone ownership (yes versus no). Chi-square tests compared the differences between current smartphone owners and non-owners by demography. For cell counts with less than the expected five, Fisher's Exact Test was applied.

Continuous variables were examined for fit between distributions and assumptions of multivariate analysis. The Kolomogorov-Smirnov one-sample goodness-of-fit test indicated that both age, $D(34) = .094$, $p = .20$, and years of smartphone ownership, $D(34) = .171$, $p = .144$, did not deviate significantly from normal. However, survey instrument results (UTAUT2, SPexp, and eHEALS) were non-normally distributed with severe negative skewness – approximately 45-50% of participants scored the maximum on each of these scales (low variability and ceiling effect). Likewise, an evaluation of the Flurry iApp metrics revealed non-normal distributions but with severe positive skewness. Flurry, which specializes in analyzing consumers' mobile device behaviors, only tracked real time access from active iApp users (those who opened the app from their study phones). Any participant identification number that was not captured in the daily Flurry summary report was considered 'inactive' and assigned zeros for the metric outcomes of that day. Over the 3-month course of data collection, 14 people (41%) had zeros for all days.

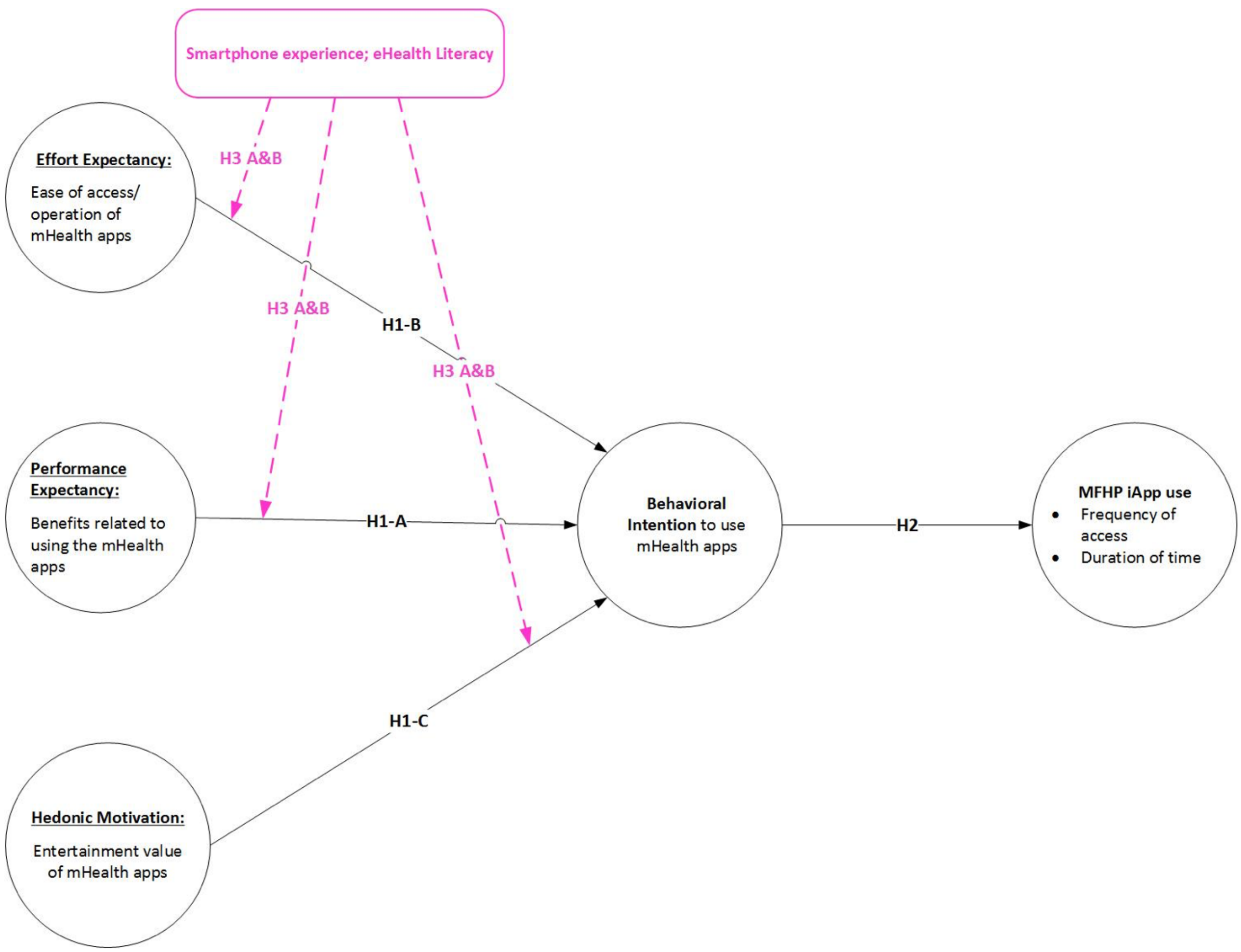
The small sample size (n = 34), extreme skewness of survey and metric results, and high percentage of zeros contained within the metric data precluded logarithmic or square root data transformations and parametric analyses. Instead, data were dichotomized to reflect the following: 1) high versus low survey scores – divided using median values, which happened to be the highest scores attainable in most of the surveys; 2) high versus low iApp access (frequency) – divided using "0" for "did not open app" and "1" for "opened app"; and 3) high versus low iApp use (duration) – divided using "0" for "did not spend time in app" and "1" for "spent time in app".

Hypothesis testing. Non-parametric techniques, as described by Pett (2016), were performed to evaluate survey/metric results and for hypothesis testing. Chi-square tests of independence assessed associations between dichotomized survey and metric variables and categorical demographics. Mann-Whitney U-tests examined group differences in survey and metric data by demography (age, years HIV-positive, race, income, and years of smartphone ownership). Wilcoxon signed rank tests were used to determine changes in individual eHEALS item scores between baseline and three months. Friedman's tests were conducted to evaluate month-to-month changes in frequency and duration of iApp use over the course of three months.

To address Aims 1- 3, Kendall's tau-b correlations were performed to determine the strength and direction of relationships between: 1) each antecedent variable and behavioral intention; 2) behavioral intention and iApp usage; and 3) smartphone experience and eHealth literacy with behavioral intent. Unlike Spearman's rho, which is calculated using variances in rank scores, Kendall's tau-b focuses on the proportion of concordant and discordant pairs of ranked data (Field, 2013; Pett, 2016). Less sensitive to error when detecting small discrepancies in rank order, it yields more conservative p-values than Spearman's rho and is the preferred nonparametric approach when analyzing small data sets containing large numbers of tied ranks (Field, 2013). Pimentel (2009) also reported that, as opposed to Spearman's rho, Kendall's tau provided a better estimation of association in data sets with zero-inflated continuous distributions. As previously described, both metric and survey results in this research were heavily tied, with data clustered in opposite extremes (zero-inflated [metric] and ceiling effect [survey]). Because of these characteristics, it was decided that Kendall's tau-b would most accurately assess the extent of associations among survey and metric variables.

A logistic regression model was intended to evaluate the moderating effects of eHealth literacy and smartphone experience on the relationship between behavioral intention and its antecedent conditions (Aim 3). Before running the regression, data were evaluated for critical assumptions (sample size relative to the number of predictor variables and collinearity). Data in this sample violated both assumptions, so logistic regression could not be performed. A more detailed description of these results is presented in Chapter 4.

Figure 4. Research model with associated hypotheses



CHAPTER 4

RESULTS

This chapter presents results of data analyses used to answer the research questions outlined in the previous chapters: 1) the associations between behavioral antecedents (effort expectancy, hedonic motivation, and performance expectancy) and behavioral intent, 2) the relationship between behavioral intent and actual use of the iApp, and 3) the moderation effects of smartphone experience and eHealth literacy on the relationship between behavioral intent and its antecedents.

Content is organized in seven sections. First, a reliability analysis of survey instruments is given. Second, sample characteristics (e.g., sample population, attrition rates) are presented. Third, general participant demographics are reported, including those of baseline smartphone ownership. Fourth, descriptive findings of survey and metric results are given. Fifth, results of findings from Wilcoxon signed rank tests and Kendall's tau-b correlations are presented to address the first research question. Sixth, results of Friedman's tests and Kendall's tau-b correlations, to address the second and third research questions, are reported. Finally, the outcomes from the moderation analysis, to address the fourth research question, are outlined.

Baseline Survey Reliability

Prior to analyzing the data, a reliability analysis was performed on all survey instruments: eHEALS, SPexp, and UTAUT2 subscales (behavioral intention [BI], effort expectancy [EE], hedonic motivation [HM], and performance expectancy [PE]). Table 5 provides a descriptive overview of all survey results at baseline and 3 months, as well as reliability scores for each of the instruments completed at baseline. Survey totals differed somewhat between baseline and 3 months but were high at both time points. As mentioned in Chapter 3, scores were extremely

Table 5

Reliability and descriptive statistics of survey instruments at baseline and 3 months

		Baseline					3 months			
Instrument	# items	Cronbach's alpha	n	Mean (SD)	Median	[Min, max]	n	Mean (SD)	Median	[Min, max]
Smartphone Experience†	10	.971	28	40.9 (13.2)	47	[10, 50]				
eHEALS	8	.954	31	34.4 (7.7)	40	[12, 40]	22	36.2 (6)	39	[16, 40]
UTAUT2										
Behavioral intention subscale	3	.799	31	19 (2.9)	21	[7, 21]	24	18.6 (2.8)	19	[12, 21]
Effort expectancy subscale	4	.935	31	24.3 (5)	28	[9, 28]	24	24.3 (5.1)	26	[8, 28]
Hedonic motivation subscale	3	.989	31	18.1 (4.2)	21	[3, 21]	24	18 (4)	19.5	[6, 21]
Performance expectancy subscale	4	.888	31	24 (5.6)	26	[4, 28]	24	24.4 (3.5)	25	[16, 28]

negatively skewed with median values at or near the maximum attainable for each survey. More detailed descriptions of each instrument's results are presented in subsequent sections.

Reliability analyses indicated good to high internal consistency for all baseline surveys. Of the UTAUT2 subscales, the 3-item BI scale had the lowest internal consistency, with a Cronbach's alpha of .799, and the 3-item HM scale had the highest internal consistency, with a Cronbach's alpha of .989. The other two UTAUT2 subscales, the 4-item EE scale and the 4-item PE scale, were also highly internally consistent with Cronbach's alphas of .935 and .888, respectively. The 8-item eHealth literacy and the 10-item smartphone experience scales were also highly internally consistent with corresponding Cronbach's alphas of .954 and .971.

Sample Characteristics

Thirty-four HIV-positive rurally dwelling Georgians were recruited and randomized into the intervention arm of the MFHP study between March 1, 2015, and February 29, 2016. Both the Augusta and Columbus sites recruited nine participants (26.5%) apiece. Brunswick recruited ten (29.4%). Athens and Macon recruited four (11.8%) and two (5.9%) participants, respectively.

Within the first 100 days of participation, three people (9%) withdrew from the study. One participant left at 68 days, and two others withdrew at 91 days. Reasons given were as follows: time commitment to study incompatible with personal schedule; study activities too complicated; concerns that cell phones cause cancer; and loss of interest. By their consent, survey and metric data were retained from the two who withdrew at 91 days. The other participant's survey and metric data, while not fully represented in the entire 3-month data collection period, were also kept by permission. This person's metric outcomes were slightly zero-inflated; however, no reweighting was necessary for analysis because there were not enough data to perform an adjustment.

Nine participants (26.5%) failed to complete the second clinic-based visit three months after their first (baseline) visit. These included the three who had withdrawn from the study. While there were no statistically significant demographic differences between those who did and did not attend the 3-month follow-up, individuals who missed the second visit were a little younger (M = 33 versus 38 years), $r_{\tau}(34) = .162$, $p = .265$ and earned a higher monthly income than participants who were seen at both time points (Mdn = \$1200 versus \$592), $r_{\tau}(31) = -.252$, $p = .098$. They also scored slightly higher on the SPexp survey, indicating higher perceived proficiency at operating smartphones, than those who kept their 3-month appointments, $r_{\tau}(31) = -.320$, $p = .060$.

Participant Demographics

Descriptive findings are described below and synopsized in tables. Table 6 summarizes both continuous and categorical demographic characteristics within the sample, including smartphone ownership. Table 7 gives a breakdown of years living with HIV by age group. Finally, Table 8 provides an overview of Kendall's tau-b intercorrelations among these characteristics.

General Characteristics

Participants were predominantly single (88%), male (62%), African American (74%), heterosexual (56%), not homeless (97%), living with others (79%), educated up to a high school level (68%), and unemployed (65%) with a median monthly income of \$735 (Table 6). Individuals ranged between 19 and 62 years of age. Because this was a normally distributed variable, age was dichotomized by the sample mean of 37 years for hypothesis testing.

Table 6

Participant demographic characteristics

	Mean (SD)	Median	Minimum	Maximum
Age at baseline	37.2 (11.4)	36	19	62
Years living with HIV	6.2 (8.1)	.58	.10	25.8
Monthly income ($)	1195 (1180)	735	0	3780
Male	869 (974)	450	0	3300
Female	1709 (1331)	1128	192	3780
Years of smartphone ownership	6.4 (5.9)	5.2	0	20.0

	Total sample (n = 34)		Did not own a smartphone at baseline*		Owned a smartphone at baseline			
	n	%	n	%	n	%	$\chi^2(1)$	*p*
Gender							1.954	0.162
Male	21	62	7	50	14	74		
Female	13	38	7	50	5	26		
Race							FET†	0.442
African American	25	74	9	64	15	79		
All other races	9	26	5	36	4	21		
Age range							6.867‡	0.076
19 - 29 years	10	29	3	21	7	37		
30 - 39 years	12	35	3	21	9	47		
40 - 49 years	6	18	3	21	2	11		
50+ years	6	18	5	36	1	5		
Sexual identity							0.203	0.653
Heterosexual	19	56	7	50	11	58		
Homosexual/Bisexual	15	44	7	50	8	42		
Marital status							FET†	1.000
In relationship	4	12	1	7	2	11		
No relationship	30	88	13	93	17	89		
Living arrangement							FET†	0.422
Live alone	7	21	4	29	3	16		
Live with others	27	79	10	71	16	84		
Education							FET†	0.698
HS/GED or less	24	71	11	79	13	68		
College or more	10	29	3	21	6	32		
Employment							FET†	0.278
Unemployed	22	65	11	79	11	58		
Employed	12	35	3	21	8	42		

* Participants who specified not owning mobile device at baseline or owned a cellphone that was not a smartphone.
†Fisher's Exact Test.
‡$\chi^2(3)$.

The time between the initial HIV diagnosis and entrance into the study ranged between one month and nearly 26 years (*Mdn* = .58 years). As shown in Table 7, participants between the ages of 19 and 29 years reported the shortest time since diagnosis (*Mdn* = .3 years), and those aged between 40 and 49 years lived with HIV the longest (*Mdn* = 17.1 years). Higher incidences of new HIV diagnoses are typically associated with youth; however, it is important to note that in this sample, all age groups contained individuals who were diagnosed less than six months prior to baseline. Nonetheless, younger participants were more likely to be newly diagnosed or living with HIV for substantially fewer months/years than older participants, $r_\tau(34) = .410$, $p = .001$ (Table 8). There were no other correlations with amount of time living with HIV.

Table 7
Years since initial HIV diagnosis

Age Range	n	Mean (SD)	Median	Minimum	Maximum
19 – 29 years	10	0.9 (2)	0.3	0.1	6.6
30 – 39 years	12	3.8 (5.2)	0.6	0.2	13.6
40 – 49 years	6	15.8 (8.4)	17.1	0.3	25.8
50 + years	6	10.3 (10)	8.5	0.3	25.8

Job status was not correlated with any demographic characteristic, but income was significantly associated with both employment and level of education. Individuals who were employed earned significantly more than the median monthly income of $735, $r_\tau(34) = .346$, p = .034. Moreover, those with college-level educations were likely to be higher wage earners, $r_\tau(31) = .395$, $p = .010$. Although the monthly income for African Americans was less than participants of other races (*Mdn* = $700 versus $1151.50), the association between race and income was *not* statistically significant, $r_\tau(34) = .286$, $p = .061$. Race was not significantly correlated with any other demographic characteristic.

Table 8

Kendall's tau-b intercorrelations among demographic characteristics

	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Age	--												
2. Gender	**.320***	--											
3. Sexual identity	**-.298***	**-.577****	--										
4. Years HIV+	**.410****	.050	-.165	--									
5. Race	.051	.077	.272	-.218	--								
6. Education	.118	.289	-.184	.062	-.241	--							
7. Marital status	.152	-.088	-.227	.099	-.195	.035	--						
8. Live w/ others	-.143	.101	-.134	-.171	-.024	-.150	-.186	--					
9. Employment	-.089	.052	.087	.016	.254	.064	-.112	-.081	--				
10. Income	.138	**.300***	-.151	-.102	.286	**.395****	-.143	-.140	**.346***	--			
11. Own smartphone	**-.288***	-.243	-.078	0	-.163	.113	-.058	.155	.217	.123	--		
12. Years smartphone ownership	-.172	-.146	.293	.049	-.079	.139	.236	-.022	.147	.171	.	--	
13. Smartphone experience (self-report)	-.240	.045	.053	-.064	-.275	**.362***	.105	.112	.030	.261	.253	**.382***	--

* p ≤ 0.05.

** p ≤ 0.01.

There were notable gender differences within the sample. Women reported higher monthly incomes than men (*Mdn* = \$1127 versus \$450), $r_\tau(31) = .300$, p = .049 (Tables 6 and 8). Independent samples t-tests revealed that males were significantly younger than their female counterparts (*M* = 34.1 versus 42.2 years), $t(32) = -2.14$, $p = .040$. Moreover, most men (67%) self-identified as homosexual or bisexual, as opposed to women (8%), $r_\tau(34) = -.577$, $p = .001$. While not statistically significant, more women attended college than men (46% versus 19%).

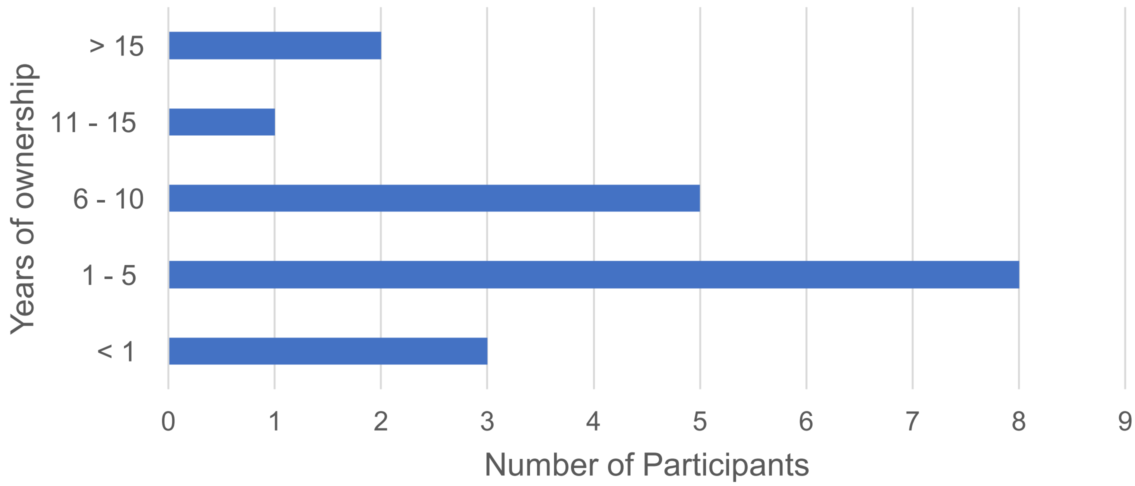
Smartphone Ownership

Aside from general demographic information, Table 6 also presents a breakdown of sample characteristics by smartphone ownership. At baseline, 19 (56%) participants owned a smartphone. Duration of smartphone ownership, also normally distributed, ranged from 1 week to 20 years (*M* = 6.4 years, *SD* = 5.9). Smartphones have been on the market since the early-to-mid-2000's, yet two individuals reported having owned one for over 15 years (Figure 5) – these answers most likely reflect cellphone, not smartphone, ownership. Smartphone owners were predominantly male (74%), African American (79%), heterosexual (58%), single (89%), high school graduates (68%), and unemployed (58%). Chi-square tests of independence revealed that none of these variables appreciably differed between smartphone owners and non-owners; however, an independent samples t-test showed that owners were significantly younger than non-owners (*M* = 33.1 versus 42.9 years), $t(31) = 2.33$, $p = .027$, $d = .84$. Eighty-four percent of owners were aged less than 40 years and 5% were older than age 50.

Survey and Metric Results

The following section presents a descriptive analysis of survey and metric findings. Mann-Whitney U-tests were employed to evaluate survey instrument results (UTAUT2, SPexp, and eHEALS) and Flurry metric usage. In addition, common mobile activities of smartphone owners and non-owners were compared. Finally, Wilcoxon Signed Rank Tests were performed to examine changes in eHealth literacy from baseline to 3 months.

Figure 5. Self-reported length of smartphone ownership at baseline



UTAUT2 Survey

Chi-square tests of independence showed no significant differences in UTAUT2 subscale totals at baseline, indicating that acceptance/adoption of the iApp was comparable among all participants by categorical demographic groups. However, age constituted one of the most significantly differentiating variables between high-scoring and low-scoring survey groups (Table 9). Those who were younger reported stronger beliefs that mHealth apps: 1) are easy and accessible to use (EE); 2) are enjoyable to use (HM); and 3) can help them stay healthy (PE). In addition, younger people generally expressed greater behavioral intent to use the iApp than those who were older.

The length of smartphone ownership, measured in years, also significantly differed between some high- and low-scoring groups. People who indicated that smartphone apps were user friendly (EE) owned their smartphones significantly longer than those who found smartphone apps more difficult to navigate (*Mdn* = 6.42 versus 1.10 years), z = 2.113, p = .035, r = .48. Similarly, participants who enjoyed using smartphone apps (HM) owned their phones longer than participants who were less enthusiastic about app use (*Mdn* = 6.42 versus 1.10 years), z = 2.113, p = .035, r = .48. Apart from EE and HM, no other survey responses significantly differed by the amount of time a participant owned his/her phone.

Flurry Metrics

Table 9

Demographic differences by dichotomized baseline survey scores

	Low Scores		High Scores		Mann-Whitney		
Survey	Mdn	IQR	Mdn	IQR	U	*p*	*r*
eHEALS							
Age	41	16	31	11	63.50	**.006**	.47
Years HIV+	.83	16.42	0.33	13.25	117.50	.383	.15
Monthly income ($)	826	1707	733	2003	114.50	.858	.03
SP Ownership (yrs)	3.26	4.46	7.64	10.16	55.00	.272	.19
UTAUT2: Behavioral Intent (BI)							
Age	45	20	31	12	72.00	**.014**	.42
Years HIV+	7.75	17.33	0.33	6.33	116.00	.355	.16
Monthly income ($)	916	1485	593	1756	100.00	.496	.12
SP Ownership (yrs)	6.00	8.94	5.56	7.75	56.00	.136	.26
UTAUT2: Effort Expectancy (EE)							
Age	41	20	31	12	72.00	**.014**	.42
Years HIV+	7.75	17.33	0.42	6.33	111.50	.279	.19
Monthly income ($)	734	1741	735	1752	128.00	.659	.08
SP Ownership (yrs)	1.10	8.77	6.42	8.45	67.00	**.035**	.48
UTAUT2: Hedonic Motivation (HM)							
Age	41	20	31	12	72.00	**.014**	.42
Years HIV+	7.75	17.33	0.42	6.33	111.50	.279	.19
Monthly income ($)	734	1741	735	1752	128.00	.659	.08
SP Ownership (yrs)	1.10	8.77	6.42	8.45	67.00	**.035**	.48
UTAUT2: Performance Expectancy (PE)							
Age	41	21.25	33.00	13.50	75.50	**.018**	.41
Years HIV+	2.00	16.65	0.38	7.77	132.00	.677	.07
Monthly income ($)	734	1532	735	2385	138.50	.464	.13
SP Ownership (yrs)	2.50	7.82	7.29	9.94	65.00	.083	.40

Chi-square tests of independence were used to evaluate dichotomized iApp frequency/duration metrics by categorical demographics. Results indicated no significant differences in the frequency or duration of overall iApp use by any demographic characteristic. Next, Mann-Whitney U tests were conducted to compare the frequency and duration of iApp use by age, years living with HIV, monthly income, and length of smartphone ownership. No significant differences emerged when examining frequency and duration by age, income, or length of ownership; however, newly diagnosed participants opened the iApp significantly fewer times than those who had been living with HIV for a longer period (Table 10). The same was true for time spent in the iApp. Participants who were recently diagnosed spent fewer minutes using the app versus those who had been living with HIV for several years (Table 11). When broken down by in-app modules (program manual, music/talk segments, pill count survey, and music videos), all but the video portion differed significantly by the amount of time since initial HIV diagnosis.

Smartphone Experience

Twenty-eight participants (82%) completed the baseline SPexp. Six respondents owned a cellphone, 19 owned a smartphone, and three owned no mobile device. Survey totals for this ten-item, five-point Likert scale ranged from 10 to 50 (Table 5). The median score of 47 was near the maximum attainable, indicating high overall self-reported proficiency at operating the common mobile device features listed in Table 12. Except for degree of educational attainment and length of smartphone ownership, total smartphone experience was similar among all demographic groups (Table 8). Individuals with at least some college reported better overall

Table 10

Demographic differences by dichotomized iApp frequency

	Did Not Open		Opened at Least Once		Mann-Whitney		
	Mdn	IQR	Mdn	IQR	U	*p*	*r*
Overall (all modules)							
Age	31.00	18.00	37.00	17.00	176.00	.161	.24
Years HIV+	.25	0.13	6.58	14.75	206.00	**.013**	.42
Monthly income ($)	733	2103	735	1707	110.00	.779	.05
SP Ownership (yrs)	6.24	16.37	3.89	6.77	44.00	1.000	0.00
Manual module							
Age	33.00	16.50	38.00	17.50	182.50	.190	.22
Years HIV+	.25	2.13	7.75	16.75	209.00	**.025**	.38
Monthly income ($)	847	2396	735	1676	110.50	.707	.07
SP Ownership (yrs)	7.64	12.07	3.26	5.16	36.00	.462	.17
Music module							
Age	30.00	15.50	37.50	16.50	189.00	.086	.29
Years HIV+	.25	.10	7.17	15.40	218.00	**.006**	.47
Monthly income ($)	733	2103	735	1707	124.00	.779	.05
SP Ownership (yrs)	7.29	14.37	3.58	6.17	39.00	.624	.11
Survey module							
Age	33	13.00	38	18.00	183.00	.160	.24
Years HIV+	.25	3.75	6.58	16.33	202.00	**.038**	.36
Monthly income ($)	733	2800	735	1532	117.50	.921	.02
SP Ownership (yrs)	6.24	11.19	3.89	7.38	44.00	.935	.02
Video module							
Age	35	19.50	38	17.50	166.50	.287	.18
Years HIV+	.333	10.79	6.58	14.791	167.00	.277	.19
Monthly income ($)	700	1406	826	1934	130.50	.503	.12
SP Ownership (yrs)	7.29	7.82	2.96	5.62	31.00	.483	.16

Table 11

Demographic differences by dichotomized iApp duration

	Spent No Time		Spent Time		Mann-Whitney		
	Mdn	IQR	Mdn	IQR	U	*p*	*r*
Overall (all modules)							
Age	32.00	15.50	37.50	17.75	180.00	.161	.24
Years HIV+	.25	1.02	7.17	15.54	206.00	**.020**	.40
Monthly income ($)	847	2877	735	1388	112.50	.796	.05
SP Ownership (yrs)	7.29	13.78	3.58	7.08	42.00	.806	.06
Manual module							
Age	33.00	16.50	38.00	17.50	182.50	.190	.22
Years HIV+	0.25	2.13	7.75	16.75	209.00	**.025**	.38
Monthly income ($)	847	2396	735	1676	110.50	.707	.07
SP Ownership (yrs)	7.64	12.07	3.26	5.16	36.00	.462	.17
Music module							
Age	31.00	13.00	38.00	18.00	192.00	.086	.29
Years HIV+	0.25	0.08	7.75	16.25	217.00	**.009**	.45
Monthly income ($)	847	2877	735	1388	112.50	.796	.05
SP Ownership (yrs)	7.64	12.07	3.26	5.16	36.00	.462	.17
Survey module							
Age	32.00	15.50	37.50	17.75	180.00	.161	.24
Years HIV+	0.25	1.02	7.17	15.54	206.00	**.020**	.40
Monthly income ($)	847	2877	735	1388	112.50	.796	.05
SP Ownership (yrs)	7.29	13.78	3.58	7.08	42.00	.806	.06
Video module							
Age	34.00	18.75	48.25	17.25	177.50	.189	.23
Years HIV+	0.33	7.13	7.17	16.58	185.00	.113	.27
Monthly income ($)	700	1406	826	1637	130.50	.503	.12
SP Ownership (yrs)	6.24	8.80	3.89	6.81	38.00	.735	.08

Table 12

Proportion of mobile activities at baseline by device ownership

	Total (n = 28)		No smartphone (n = 9)		Smartphone (n = 19)			
	n	%	n	%	n	%	$\chi^2(1)$†	*p*
Send or receive email							FET‡	0.420
Never/Less than once weekly	8	29	4	44	4	21		
1-6 days a week	6	21	2	22	4	21		
Every day	14	50	3	33	11	58		
Send or receive text messages							FET‡	0.064
Never/Less than once weekly	4	14	2	22	2	11		
1-6 days a week	2	7	2	22	0	0		
Every day	22	79	5	56	17	89		
Send or receive picture messages							FET‡	0.371
Never/Less than once weekly	5	18	2	22	3	16		
1-6 days a week	3	11	2	22	1	5		
Every day	20	71	5	56	15	79		
Send or receive video messages							FET‡	0.210
Never/Less than once weekly	8	29	5	56	3	16		
1-6 days a week	2	7	0	0	2	11		
Every day	18	64	4	44	14	74		
Take pictures							FET‡	0.407
Never/Less than once weekly	4	14	2	22	2	11		
1-6 days a week	5	18	2	22	3	16		
Every day	19	68	5	56	14	74		
Listen to music							FET‡	0.371
Never/Less than once weekly	5	18	3	33	2	11		
1-6 days a week	3	11	1	11	2	11		
Every day	20	71	5	56	15	79		
Watch videos							FET‡	0.407
Never/Less than once weekly	5	18	2	22	3	16		
1-6 days a week	4	14	2	22	2	11		
Every day	19	68	5	56	14	74		
Download and use apps							FET‡	1.000
Never/Less than once weekly	9	32	3	33	6	32		
1-6 days a week	2	7	1	11	1	5		
Every day	17	61	5	56	12	63		
Access the Internet							FET‡	0.165
Never/Less than once weekly	5	18	2	22	3	16		
1-6 days a week	2	7	2	22	0	0		
Every day	21	75	5	56	16	84		
Browse websites							FET‡	0.371
Never/Less than once weekly	6	21	3	33	3	16		
1-6 days a week	2	7	1	11	1	5		
Every day	20	71	5	56	15	79		

†Categories collapsed to two levels: "Never to 6 days a week" and "Every day."
‡Fisher's Exact Test.

expertise using smartphones than persons who were educated through high school or less, $r_\tau(28) = .362$, $p = .033$. Those who owned their smartphones longer reported greater self-perceived expertise operating their devices, $r_\tau(19) = .382$, $p = .033$.

To evaluate specific dimensions of self-reported smartphone expertise, Mann-Whitney U-tests were performed comparing each survey item by categorical demographic characteristics. Age (dichotomized by the sample mean of 37 years) and race revealed multiple significant item-by-item differences. Younger participants sent/received picture and video messages, listened to music, watched videos, accessed the Internet, and browsed websites more than their older counterparts (Table 13). As opposed to other races/ethnicities, African American participants listened to music, watched videos, and downloaded apps more frequently (Table 14). Persons with a college education sent/received emails significantly more from those with a high school education or less (*Mdn* score = 5 versus 4), U = 98.5, z = 1.957, *p* = .050.

Table 13

Age differences in individual SPexp item scores

	Less than 37 years †		37 years or greater		Mann-Whitney		
Survey Item	Mdn	IQR	Mdn	IQR	U	*p*	*r*
Send or receive email	4.50	3.00	4.50	4.00	84.00	.757	.06
Send or receive text messages	5.00	0.00	5.00	1.75	65.00	.095	.32
Send or receive picture messages	5.00	0.00	4.50	4.00	57.50	**.050**	.37
Send or receive video messages	5.00	0.25	2.00	4.00	49.00	**.021**	.44
Take pictures	5.00	0.25	4.50	3.25	61.00	.093	.32
Listen to music	5.00	0.00	4.00	4.00	54.50	**.033**	.40
Watch videos	5.00	0.00	3.50	4.00	50.00	**.021**	.44
Download and use apps	5.00	1.50	3.00	4.00	55.00	.056	.36
Access the Internet	5.00	0.00	4.50	4.00	54.00	**.023**	.43
Browse websites	5.00	0.00	4.50	4.00	56.50	**.044**	.38

† Age dichotomized by sample mean of 37 years

Smartphone experience by device ownership. SPexp results indicated that smartphone owners and non-owners were comparably experienced operating most common mobile functions, except for sending/receiving email and downloading/using apps (Table 15). Among those who did not own a smartphone, emailing was not significantly associated with any mobile activity, nor was app usage correlated with Internet access or browsing websites. For those who did own smartphones, longer length of ownership positively correlated with text messaging, $r_\tau(19) = .446$, $p = .024$, and browsing website, $r_\tau(19) = .389$, $p = .042$.

Table 14

Race/ethnicity differences in individual SPexp item scores

	African American		Other race/ethnicity		Mann-Whitney		
Survey Item	Mdn	IQR	Mdn	IQR	U	*p*	*r*
Send or receive email	5.00	3.00	4.00	3.5	66.50	.460	.14
Send or receive text messages	5.00	0.00	5.00	2.5	63.00	.228	.23
Send or receive picture messages	5.00	0.75	5.00	2.5	70.00	.523	.12
Send or receive video messages	5.00	2.50	4.00	3.0	68.00	.475	.14
Take pictures	5.00	0.75	4.50	2.8	59.50	.208	.24
Listen to music	5.00	0.00	3.50	2.8	47.00	**.035**	.40
Watch videos	5.00	0.00	3.00	2.8	48.50	**.053**	.37
Download and use apps	5.00	0.75	2.00	3.3	35.50	**.010**	.49
Access the Internet	5.00	0.75	5.00	2.3	78.50	.920	.02
Browse websites	5.00	0.75	5.00	2.8	70.50	.544	.11

Mobile features most frequently accessed daily by both groups included sending/receiving text messages, browsing the Internet, sending/receiving picture messages, browsing websites, listening to music, sending/receiving video messages, taking pictures, watching videos, and downloading/using apps (Table 12). Compared to 56% of non-owners, 63% of smartphone owners reported downloading and using mobile apps at least once a day. Sending/receiving emails was the least utilized mobile function, with only 58% (of both owners and non-owners) accessing their email accounts every day.

Table 15

Kendall's tau-b intercorrelations among SPexp survey items by device ownership†

	1	2	3	4	5	6	7	8	9	10	11
1. Length of smartphone ownership	--	--	--	--	--	--	--	--	--	--	--
2. Send/receive email	.356	--	.584	.584	.286	.573	.548	.573	.475	.358	.329
3. Send/receive text messages	.446*	.488*	--	1.000**	.745*	.981**	.960**	.981**	.880**	.667*	.640*
4. Send/receive picture messages	.161	.683**	.659**	--	.745*	.981**	.960**	.981**	.880**	.667*	.640*
5. Send/receive video messages	.270	.703**	.625**	.862**	--	.692*	.824**	.692*	.667*	.692*	.706*
6. Use camera	.250	.705**	.598**	.893**	.949**	--	.902**	1.000**	.902**	.615*	.588
7. Listen to music	.351	.648**	.277	.462*	.594**	.586**	--	.902**	.800*	.667*	.640*
8. Watch videos	.364	.613**	.602**	.674**	.568**	.573**	.632**	--	.902**	.615*	.588
9. Download/use apps	.346	.658**	.448*	.661**	.767**	.746**	.735**	.774**	--	.510	.480
10. Access Internet	.281	.658**	.752**	.877**	.774**	.780**	.561*	.801**	.625**	--	.981**
11. Browse websites	.389*	.730**	.659**	.754**	.650**	.656**	.723**	.899**	.698**	.877**	--

†Note. Intercorrelations for smartphone non-owners (n = 9) are presented above the diagonal, and intercorrelations for smartphone owners (n = 19) are presented below the diagonal.

* $p \leq 0.05$.

** $p \leq 0.01$.

eHealth Literacy

Thirty-one participants (91.1%) took the eHealth Literacy Scale (eHEALS) at the baseline visit and 22 (64.7%) completed it at the three-month follow-up. At baseline, all categorical demographic groups scored similarly on the eHEALS instrument except for race. African Americans perceived themselves to possess better eHealth literacy (89.5%) than did non-African Americans (10.5%), $p = .025$ (Fisher's Exact Test). A Mann-Whitney U-test revealed that younger individuals also reported significantly higher perceived eHealth literacy than those who were older (Table 9).

eHealth literacy over time. Survey totals for this eight-item, five point Likert scale ranged from 12 to 40 at baseline and 16 to 40 at 3 months, with higher scores indicating better eHealth literacy (Table 5). Wilcoxon signed-rank tests were performed to evaluate changes in scale items between baseline and 3 months among the 22 participants who completed the eHEALS at both time points. Results were stratified by age (dichotomized by the sample mean of 37 years) and race/ethnicity, both of which were significantly associated with differences in individual item totals (Table 16). Item scores were lower among older participants than the sample medians at baseline. Younger participants' scores were the highest attainable for each item. As opposed to their younger counterparts (whose median scores remained unchanged), those who were older reported statistically significant increases at 3 months in several content areas: knowing what health resources are available on the Internet, knowing how to get answers for health-related questions using the Internet, and knowing how to use health information from the Internet for health benefits. Although not statistically significant, older participants also reported improvements in their ability to assess the quality of Internet-based health information.

Table 16

Wilcoxon signed rank test of baseline versus 3-month eHEALS scores by age and race

	Total Sample	Age[†]		Race	
eHEALS Item (scale range 1 - 5)		Less than 37 years	37 years or greater	African American	Other
I know what health resources are available on the Internet					
Median score at baseline / 3-months	5.00 / 5.00	5.00 / 5.00	3.00 / 5.00	5.00 / 5.00	3.00 / 4.50
Z-score	-2.683	-1.069	-2.598	-1.511	-2.251
Significance (2-tailed)	**.007**	.500	**.008**	.250	**.031**
I know where to find helpful health resources on the Internet					
Median score at baseline / 3-months	5.00 / 5.00	5.00 / 5.00	3.50 / 4.50	5.00 / 5.00	3.50 / 4.50
Z-score	-1.513	-.577[a]	-1.933	.000	-2.121
Significance (2-tailed)	.186	1.000	.094	1.000	.063
I know how to find helpful resources on the Internet					
Median score at baseline / 3-months	5.00 / 5.00	5.00 / 5.00	4.00 / 5.00	5.00 / 5.00	4.00 / 4.50
Z-score	-1.811	.000	-1.933	-.378[b]	-2.121
Significance (2-tailed)	.113	1.000	.094	1.000	.063
I know how to use the Internet to answer my questions about health					
Median score at baseline / 3-months	5.00 / 5.00	5.00 / 5.00	4.00 / 5.00	5.00 / 5.00	4.00 / 5.00
Z-score	-2.309	-.577[b]	-2.333	-.816	-2.449
Significance (2-tailed)	**.035**	1.000	**.031**	.750	**.031**
I know how to use the health information I find on the Internet to help me					
Median score at baseline / 3-months	5.00 / 5.00	5.00 / 5.00	4.00 / 5.00	5.00 / 5.00	4.00 / 4.50
Z-score	-2.121	.000	-2.449	-1.000[b]	-2.000
Significance (2-tailed)	.070	1.000	**.031**	.625	.125
I have the skills I need to evaluate the health resources I find on the Internet					
Median score at baseline / 3-months	5.00 / 5.00	5.00 / 5.00	4.00 / 5.00	5.00 / 5.00	4.00 / 5.00
Z-score	-1.414	-1.000[a]	-1.890	.000	-2.000
Significance (2-tailed)	.289	1.000	.125	1.000	.125
I can tell high quality from low quality health resources on the Internet					
Median score at baseline / 3-months	5.00 / 5.00	5.00 / 5.00	3.00 / 4.00	5.00 / 5.00	3.00 / 4.00
Z-score	-2.081	.000	-2.121	-.447	-2.070
Significance (2-tailed)	.063	1.000	.063	1.000	.063
I feel confident in using information from the Internet to make health decisions					
Median score at baseline / 3-months	5.00 / 5.00	5.00 / 5.00	3.50 / 4.00	5.00 / 5.00	3.00 / 4.00
Z-score	-1.994	-.447[b]	-2.070	-1.518	-1.342
Significance (2-tailed)	.078	1.000	.063	.250	.500

[†]Age dichotomized by sample mean of 37 years
[a] Based on positive ranks
[b] Based on negative ranks

All median item scores were the highest attainable at baseline and 3 months among the African American participants (Table 16). Persons of other races/ethnicities scored lower at the baseline visit than the sample medians for each item. At 3 months, this group reported statistically significant increases in knowing what health resources are available on the Internet and knowing how to get answers for health-related questions using the Internet. These individuals reported (not statistically significant) gains finding and using health resources on the Internet, as well as assessing the quality of Internet-based health information.

RQ 1: Association of BI Antecedents with BI

iApp participants completed the UTAUT2 survey via ACASI during their scheduled baseline and 3-month visits. Data were collected at both time points and tested using nonparametric techniques for the following: 1) an examination of subscale score differences between the baseline and 3-month visits, and 2) hypothesis testing of the strength of association among UTAUT2 constructs from baseline surveys. This section presents the results of these tests.

Baseline and 3-month Survey Score Differences

Thirty-one of 34 (91%) participants took the UTAUT2 survey during the baseline interview, and twenty-one (68%) completed the survey at the 3-month follow-up. To assess the magnitude of changes in UTAUT2 scores between baseline and 3 months, a Wilcoxon signed-rank test was performed. Median scores were similar in all subscales at both time points (Table 5). Results confirmed that there were no significant rank differences between the baseline and 3-month interviews. Thus, the subscale scores, which were already high, remained stable over time and signaled participants' greater acceptance of and intent to use the iApp.

H1-A Through H1-C: Relationship Between BI and BI Antecedents

Kendall's tau-b coefficient was used to examine the strength of association between the baseline BI and EE, HM, and PE (Table 17). The outcome of this analysis showed that behavioral antecedent subscale scores were highly and positively correlated with behavioral intention scores: EE, $r_\tau(31) = .725$, $p = .000$; HM, $r_\tau(31) = .706$, $p = .000$; and PE, $r_\tau(31) =.675$, $p = .000$. Participants who agreed that smartphone apps were easy to access/operate (EE), fun to use (HM), and personally beneficial (PE) were also significantly motivated to use the iApp. These findings support research hypotheses H1-A through H1-C, which state that EE, HM, and PE have direct positive associations with behavioral intent to use the MFHP.

Table 17
Kendall's tau-b intercorrelations among baseline SPexp, eHEALS, and UTAUT2 scores

Scale	1	2	3	4	5	6
1. Smartphone experience	--					
2. eHEALS	.444**	--				
3. BI subscale	.494**	.398*	--			
4. EE subscale	.613**	.427**	.725**	--		
5. HM subscale	.613**	.469**	.706**	.945**	--	
6. PE subscale	.573**	.459**	.675**	.706**	.692**	--

* p ≤ 0.05.
** p ≤ 0.01.

RQ 2 and 3: Association of BI with Frequency/Duration of iApp Access

Hypothesis testing was conducted to examine the relationship between behavioral intention and the frequency/duration of iApp usage. Metric totals (in minutes) were examined to detect usage patterns or trends over the 3-month data collection period (Figures 6 and 7). Kendall's tau-b correlations were used to evaluate correlations between behavioral intention to use the iApp and the actual frequency/duration of app usage (Table 18). Results are presented in the following sections.

Metric iApp Usage Patterns

Of the 34 participants, 14 (41%) had assigned zeros in the metric outcomes for each day of the study. Another participant's metric outcomes were excessively high and constituted 69.56% of the total duration data. An examination of this person's history revealed that peak usage periods typically fell between midnight and 4 am. We concluded that the app was probably opened at bedtime but not closed before the subject fell asleep, leading to artificially inflated outcomes. This person's continuous metric data were omitted from the analysis.

Over the course of 15 weeks (this includes the ten-day grace period allotted for the three-month follow-up), the frequency and duration iApp interactions followed similar patterns. Specifically, the number of times the app was opened peaked in the first four weeks of the study, then declined over the next eleven weeks (Figure 6), with music and survey representing the most frequently accessed portions of the app. Among newly-diagnosed participants (i.e., living with HIV less than one year), both survey and music modules were opened more times within the first two weeks of the study and then steeply declined after four weeks. Beyond the four-week mark, survey and music portions of the app were still intermittently accessed, but for fewer times than the first two weeks. Manual and video modules were infrequently opened during the entire time frame. Those living with HIV for one or more years also accessed the music and survey most often during the first two weeks of the study. This group opened all modules, except for the videos, more regularly than their newly diagnosed peers. Manual access peaked in the number of openings around five to six weeks and then declined to almost zero thereafter. The video module was rarely opened.

Mirroring the frequency data, minutes spent in the app also peaked in the first four weeks of the study and was concentrated in the music and survey modules (Figure 7). However, use of the music module varied between the two groups, with newly diagnosed participants dedicating more time listening to the songs between baseline and four weeks. After four weeks, the number of minutes spent listening to music flattened to almost zero (except for one spike around the eight-week mark). Newly diagnosed participants who took the monthly surveys spent less time answering survey questions, which may reflect better proficiency operating the app and smartphone. Those living with HIV for one or more years listened to music more consistently over the first nine weeks but for less total time. After nine weeks, time spent in the music module decreased to almost zero. They also answered the surveys more regularly than their newly-diagnosed counterparts but took more time to complete the questionnaires. Minutes spent using the iApp's manual and the video sections remained low in both groups throughout the study.

To further investigate changes in iApp usage over time, Friedman's tests were conducted looking at month-to-month frequency and duration. There was a statistically significant difference in the number of times the iApp was opened during the 3-month time-frame, $\chi^2(2) = 22.085$, p = .000. Wilcoxon signed-rank tests were performed for post hoc analysis using a Bonferroni correction, resulting in a significance level set at $p < .017$. Median (IQR) number of times the iApp was opened in month one, month two, and month three were 2 (14.50), 0 (2), and 0 (1), respectively. The app was opened significantly less times between the first and second month ($z = -3.224$, $p = .001$) and the first and third month ($z = -3.727$, $p = .000$), but there were

Figure 6. Frequency of iApp Access During the First 15 Weeks of Participation

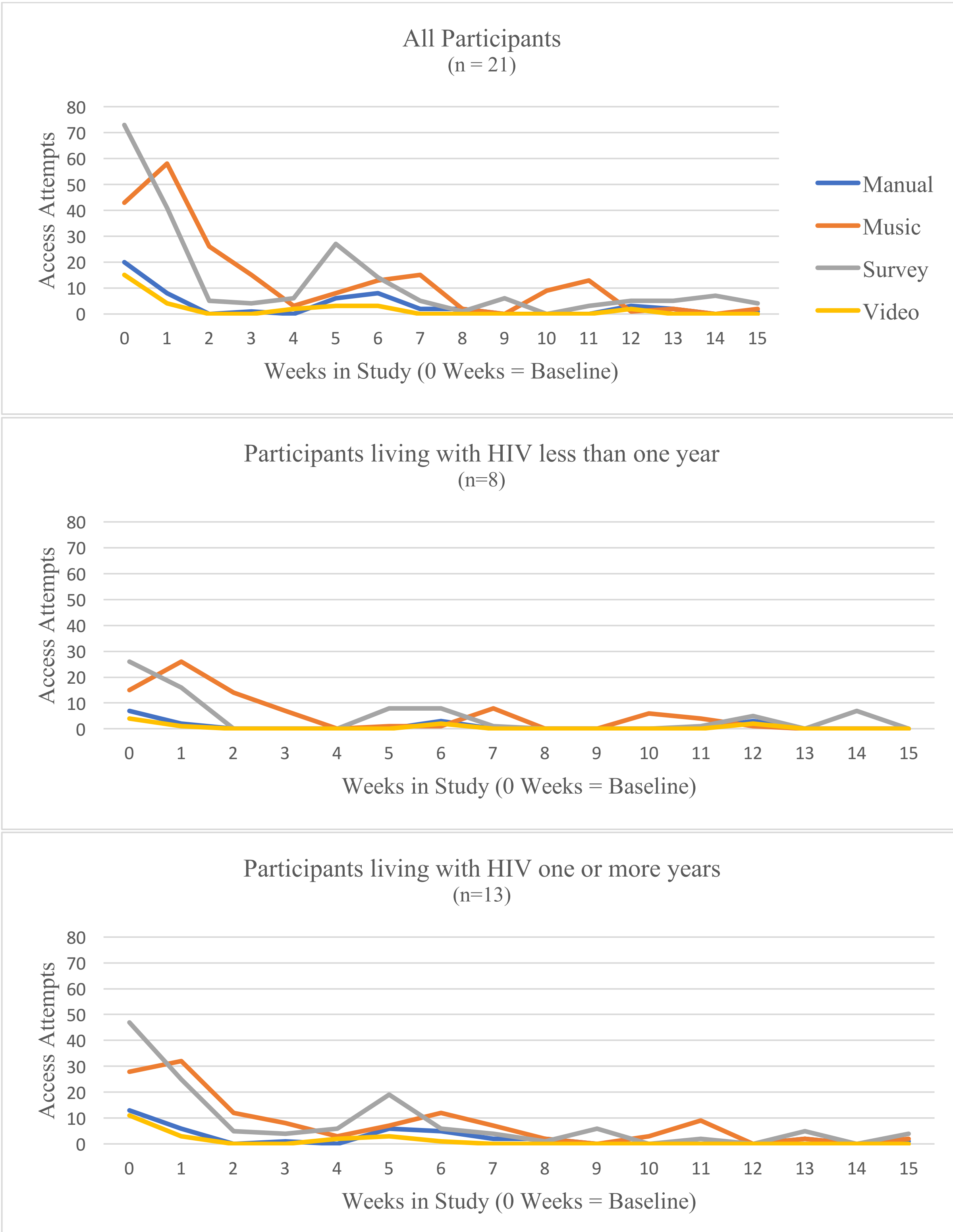
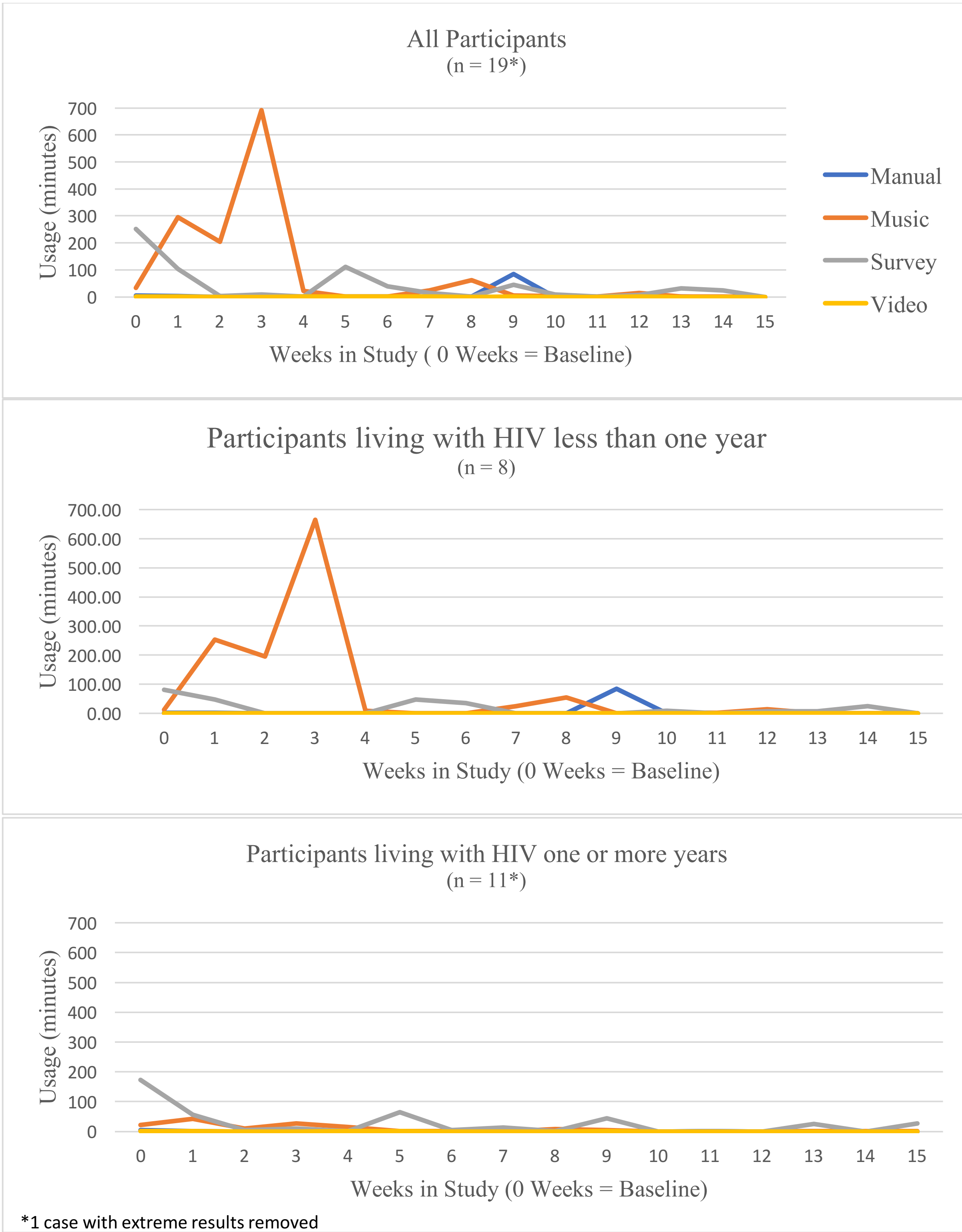


Figure 7. iApp Usage (in Minutes) During the First 15 Weeks of Participation



no significant differences in the number of times the app was accessed between the second and third month (z = -.737, p = .461).

When evaluating the duration of app use, results indicated that there was a significant change in the amount of time spent using the iApp over the first 3 months of study participation, $\chi^2(2) = 14.732$, p = .001. Wilcoxon signed-rank tests were performed for post hoc analysis with a Bonferroni correction applied, resulting in a significance level set at $p < .017$. Median (IQR) usage in minutes for month one, month two, and month three were 11.8 (26.59), 0 (13.57), and 0 (7.52), respectively. There were statistically significant reductions in the amount of time spent using the iApp between months one and two (z = -2.495, p = .013) and between months one and three (z = -3.139, p = .002); however, changes in app usage between months two and three were not statistically different.

H2: Associations Between BI and Frequency of iApp Use

Kendall's tau-b coefficient was used to examine the strength of association between the baseline BI scores and the frequency of iApp use over 3 months (Table 18). The outcome of this analysis indicated that there were no significant associations between behavioral intent and overall frequency of app access, $r_\tau(31) = -.239$ p = .190, meaning that increased intent to use the iApp did not affect the number of times it was opened. Thus, the results do not support research hypothesis H2, which states that behavioral intent will be positively associated with the number of times the iApp is accessed.

H3: Associations Between BI and Duration of iApp Use

Kendall's tau-b coefficient was also used to examine the strength of association between the baseline BI scores and the duration of iApp use over 3 months (Table 18). Like the frequency results, there were no significant associations between behavioral intent and the overall duration of app use, $r_\tau(31) = -.300$ $p = .101$. Participants who indicated that they were strongly motivated to use the iApp did not spend significantly more time using any portion of the app over the course of the study. These findings do not support research hypothesis H3, which states that behavioral intent will be positively associated with the amount of time spent using the iApp.

RQ 4: Moderating Effects of eHealth Literacy and Smartphone Experience

Finally, the influence of eHealth literacy and smartphone experience on BI were addressed. Data were evaluated prior to moderation testing. Results are presented in this final section.

Data Evaluation

Data were assessed for critical assumptions prior to employing logistic regression for moderation testing. First, the sample size was evaluated relative to the number of predictors. According to Field (2013), a rough rule of thumb is to have a ratio of 10 to15 cases for each predictor in a regression model to achieve a medium effect size. The model in this study contained five independent variables (eHealth literacy, smartphone experience, EE, HM, and PE); therefore, a minimum of 50 to 75 cases would be needed to conduct hypothesis testing. The sample size of 31 in the present study was far less than recommended.

Next, associations were examined among variables of interest. As shown in Table 17, baseline eHealth literacy, smartphone experience, BI, EE, HM, and PE were significantly and positively intercorrelated. One bivariate relationship, HM and EE, had an extremely high correlation coefficient of .945. Collinearity diagnostics were then performed with eHealth literacy, smartphone experience, and all UTAUT2 subscales included in the model. Tolerance ranged from .098 to .633, the mean variance inflation factor (VIF) was 5.09 (1.58 to 10.16), and the condition index was 82.86. All findings indicated multicollinearity. EE and HM had the highest VIFs of 10.16 and 9.78, respectively, and when they were removed from the diagnostic model, the mean VIF decreased to 1.33, with a condition index of 23.08. Although omitting these variables significantly reduced multicollinearity, dropping them from the final model would not have benefitted hypothesis testing, since the excluded variables constituted a major portion of the overall UTAUT2 model in question.

H-4A and H-4B: eHealth Literacy and Smartphone Experience as Moderators

Data in this sample violated basic assumptions for logistic regression on two fronts: 1) an insufficient ratio of cases to independent variables, and 2) a high degree of multicollinearity. Thus, hypothesis testing could not be conducted to evaluate the moderating effects of eHealth literacy and smartphone experience on the relationship between behavioral intention and its antecedent conditions. These research questions remain unaddressed.

Table 18

Kendall's tau-b intercorrelations among baseline behavioral intention scores, frequency of iApp access, and duration of iApp use

		1†	2**	3**	4**	5**	6**	7**	8**	9**	10**
	1. Behavioral Intention†	--									
Number of times app opened	2. Overall iApp frequency	-0.239	--								
	3. Manual frequency	-0.096	0.782	--							
	4. Music frequency	-0.169	0.939	0.833	--						
	5. Survey frequency	**-.360***	0.883	0.764	0.817	--					
	6. Video frequency	-0.091	0.609	0.779	0.649	0.690	--				
Amount of time spent in app	7. Overall iApp duration	-.300	0.939	0.833	0.876	0.940	0.649	--			
	8. Manual duration	-.096	0.782	1.000	0.833	0.764	0.779	0.833	--		
	9. Music duration	-.230	0.883	0.886	0.940	0.878	0.690	0.940	0.886	--	
	10. Survey duration	-.300	0.939	0.833	0.876	0.940	0.649	1.000	0.833	0.940	--
	11. Video duration	-.158	0.650	0.831	0.692	0.736	0.938	0.692	0.831	0.736	0.692

† Participants who completed the baseline UTAUT2 survey.

* $p \leq 0.05$

** all $p \leq 0.01$.

CHAPTER 5

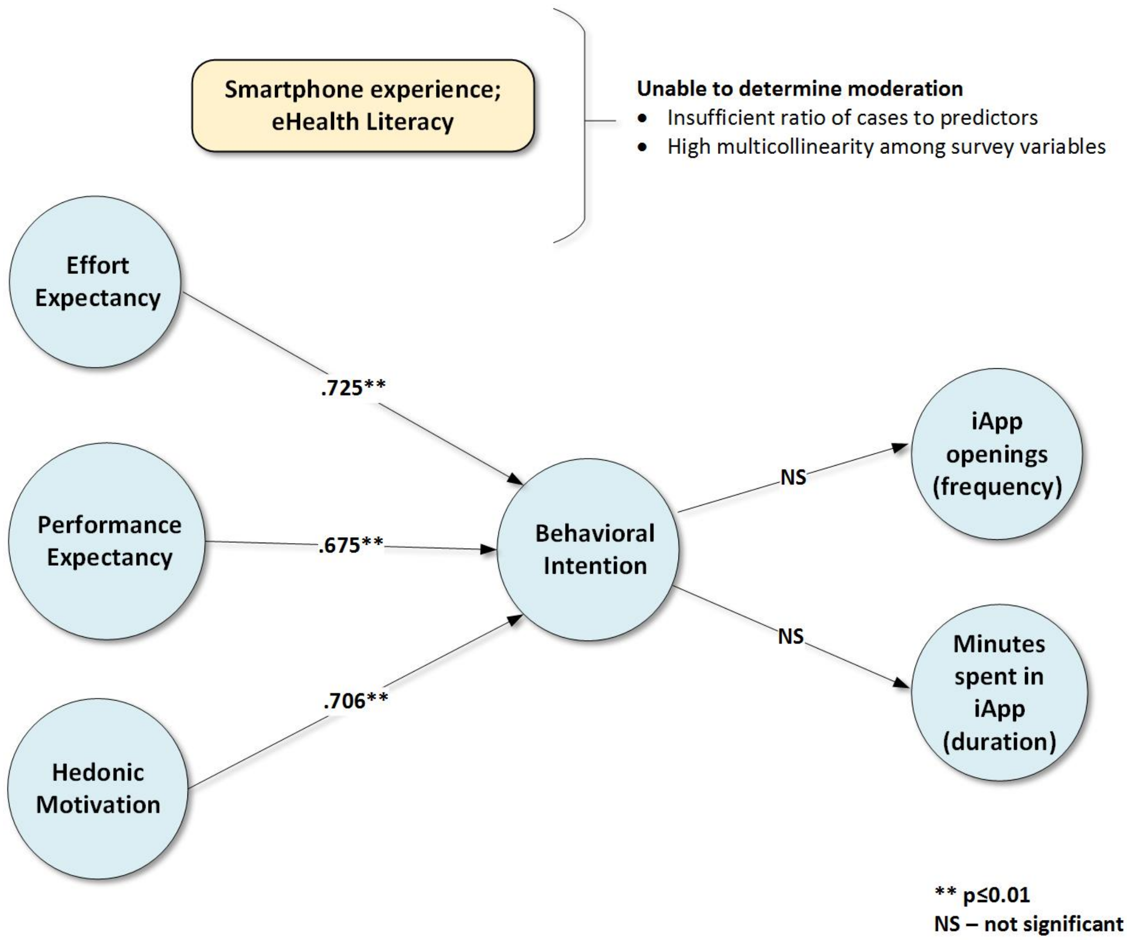
DISCUSSION

This was a secondary analysis of data from the MFHP, a randomized control study examining the efficacy of a smartphone app (iApp) designed to improve ART adherence and symptom self-management among rural dwelling PLWHA. Guided by the Modified Unified Theory of Acceptance and Use of Technology ([UTAUT2], Figure 4), the present study evaluated construct relationships posited to govern the acceptance and adoption of an mHealth app among 34 PLWHA enrolled in the intervention arm of the MFHP between March 1, 2015 and February 29, 2016. Three aims drove this research: First, to examine the associations between the behavioral intention (BI) to use the app and its antecedent conditions – effort expectancy (EE), hedonic motivation (HM), and performance expectancy (PE). Second, to determine the association between BI and the frequency/duration of iApp use. Finally, to evaluate the moderating effects of eHealth literacy/smartphone experience on the relationship between BI and its antecedent conditions.

Figure 8 illustrates the final theoretical model for this study. In summary, study findings supported the research hypotheses that each BI antecedent is strongly and positively associated with behavioral intent to use the iApp. The hypotheses that BI and iApp usage, both frequency and duration, are positively related were not supported. Last, the data were inadequate (i.e., low survey score variability and small sample size) to evaluate the moderating effects of eHealth literacy and baseline smartphone experience on the relationship between BI to use the iApp and its antecedent conditions.

This chapter presents a discussion of these findings and is divided into the following sections: a) Sample characteristics; b) iApp utilization; c) UTAUT2 and iApp use; d) Moderating factors in the UTAUT2 framework; e) Study strengths and limitations; f) Future directions; and g) Implications for research and clinical practice.

Figure 8. Final UTAUT2 model



Sample Characteristics

General Demographic Characteristics

Of the 50,000 persons living with HIV/AIDS (PLWHA) in Georgia, 68% are African American, 75% are male, 47% are homosexual/bisexual, 59% are aged 44 years or less, and 33% reside in rural counties (GDPH, 2016). Like the state's estimates, 74% of the 34 rurally dwelling PLWHA in this study were African American, 62% were male and 44% were homosexual/bisexual. Participants were younger, with 65% of the sample aged less than 40 years (M = 37 years).

The socioeconomic status of individuals within this sample also reflected that of the broader HIV-positive population living in the rural South. PLWHA living in rural settings, especially the South, experience higher disease burdens and premature mortality arising from multiple barriers: poverty, black or other minority race/ethnicity, unemployment, underinsured or no insurance, low educational attainment, restricted mobility stemming from lack of transportation, and limited access to health care (Centers for Disease Control and Prevention [CDC], 2016a, 2016b; Pellowski, 2013; Pellowski, Kalichman, Matthews, & Adler, 2013). This study's participants shared many of the barriers described above. All came from GDPH clinics that participated in the Ryan White HIV/AIDS Program, a primary mechanism through which economic burdens associated with HIV care are partially mitigated by providing poor uninsured or underinsured PLWHA access to the AIDS Drug Assistance Program and to core outpatient medical services (GDPH, 2012). Sixty-five percent were unemployed with a median monthly income of $735, which is below 200% of the federal poverty guidelines for a family size of one (Georgia Department of Community Health, 2016). Educational attainment was low, with 71% having achieved a maximum of high school or less. Compared to participants who attended at least some college, those with only primary or secondary educational backgrounds were more likely to be low wage earners or unemployed.

Anecdotally, MFHP site staff reported that some participants lacked reliable transportation to the clinics, which posed problems setting and keeping appointments. To promote visit compliance and avoid the inconvenience of repetitive clinic trips, baseline and three-month follow-up visits were coordinated, whenever possible, to occur on the same day as regularly scheduled medical appointments. A few clinics also attempted to defray travel-related expenses by giving bus passes to participants reliant on public transit.

Smartphone Ownership

Approximately 19, or 56%, of participants reported owning a smartphone at the baseline visit, lower than the national average of 68% (Anderson, 2015). According to the Pew Research Center, smartphone use in the United States approaches saturation levels among young adults, but only 18% of seniors, aged 65 years and over, own one (Smith, 2014, 2015). Congruent with these estimates, approximately 84% of smartphone owners in current study ranged between 19 and 39 years of age, and 5% were aged 50 years or more. Pew researchers also noted that disadvantaged social circumstances (e.g., less education, impoverished living conditions), chronic illness, and physical handicaps substantially contribute to sluggish technology adoption among older Americans; however, young people from comparably depressed socioeconomic conditions and minority backgrounds almost exclusively depend on smartphones for online access, entertainment, and communication (Smith, 2014, 2015). MFHP smartphone owners were predominantly young, African American, and educated at or below the high school level. Except for older age, non-owners shared the same sociodemographic characteristics.

iApp Utilization

Overall iApp Usage

The parent MFHP study was developed with the assumption that providing no-cost resources to research subjects would promote app usage; therefore, participants were supplied with free smartphones and free mobile/data service for the duration of the nine-month study. This concept is not without precedent – previous research indicates that patients with chronic illnesses are more likely to use eHealth technologies if they have ready access to resources and technology support (Fox, 2007; Gordon & Hornbrook, 2016). Nevertheless, Flurry metrics indicated that cumulative iApp utilization was low, with a large proportion of participants registering either minimal or no use. Although these results ran counter to researchers' expectations, one recent study reported similar outcomes. In their examination of factors motivating the use of electronic health record (EHR) patient portals, Tavares and Oliveira (2016) found that resource availability (i.e., a computer with an internet connection) did not significantly influence the frequency of EHR access. The authors attributed some of these findings to a younger study population with a lower proportion of chronic illnesses and less perceived need for regularly using EHR portals. In the present study, over half the participants were younger than age 40, and a significant proportion of these were newly diagnosed with HIV within a year prior to entrance into the study. Although HIV is considered a chronic condition, they may have perceived less need for an mHealth app designed to improve lifelong disease management. This could be especially true in the absence of disease-related symptoms or diminished quality of life.

Among individuals who did spend time in the iApp, frequency and duration of use peaked around four weeks, then steadily declined to almost no use toward the end of three months. This was particularly evident when looking at the music and survey module metrics – manual and video usage remained low throughout the study's timeframe. Scant eHealth research exists to compare usage statistics among mHealth apps, partly because academic studies rarely employ real-time metrics. However, a sizeable body of market research focuses on the concept of consumer mobile app stickiness (MASS), defined as "the time users spend interacting with specific apps and how often users return to a specific app to accomplish specific tasks" (Furner, Racherla, & Babb, 2014). Marketing studies consistently highlight the ephemerality of MASS by demonstrating globally limited app lifespans. In a review of 30 million downloads from Apple's App Store, Yardley (2009) reported reductions in user retention to approximately 1% by the end of the third month after downloading an app. Google's research division, thinkwithGoogle (2015), estimated that 25% of smartphone apps are never used after downloading and 38% of required apps (i.e., apps that are necessary to complete a specific task, like making a purchase) are abandoned immediately after initial use. iApp usage in the present study paralleled the short-lived consumer behaviors described above.

Characteristics of iApp Non-Users

One significant and defining characteristic of iApp 'non-users' (i.e., those without recorded Flurry metrics) was a relative inexperience managing HIV, with most having been diagnosed for only a few months prior to entering the study. Though not statistically significant, most non-users were younger than the mean age of 37 years, African American, unemployed, educated to high school or less, and missed their three-month follow-up study visits more frequently than those who used the app. Even though this research was not focused on health behaviors or outcomes, demographic characteristics of iApp non-users were consistent with those of nonadherent PLWHA. For example, in their examination of medication adherence and retention-in-care among HIV-infected young people aged 24 years or less, Kahana et al. (2016) reported significant associations between missed ART doses/appointments and poverty, racial minority, unemployment, and educational attainment of high school or less. Another study estimated that roughly 20% of newly diagnosed HIV-infected patients will not seek to establish care after their initial visit, particularly those who are African American, younger than 40 years, or contracted HIV through homosexual contact/intravenous drug use (Fleishman et al., 2012). The above research findings combined with this study's overall low app usage suggest that despite their high risk of adverse health outcomes, newly diagnosed MFHP participants may be less inclined to engage with the iApp than their older counterparts more experienced with disease self-management.

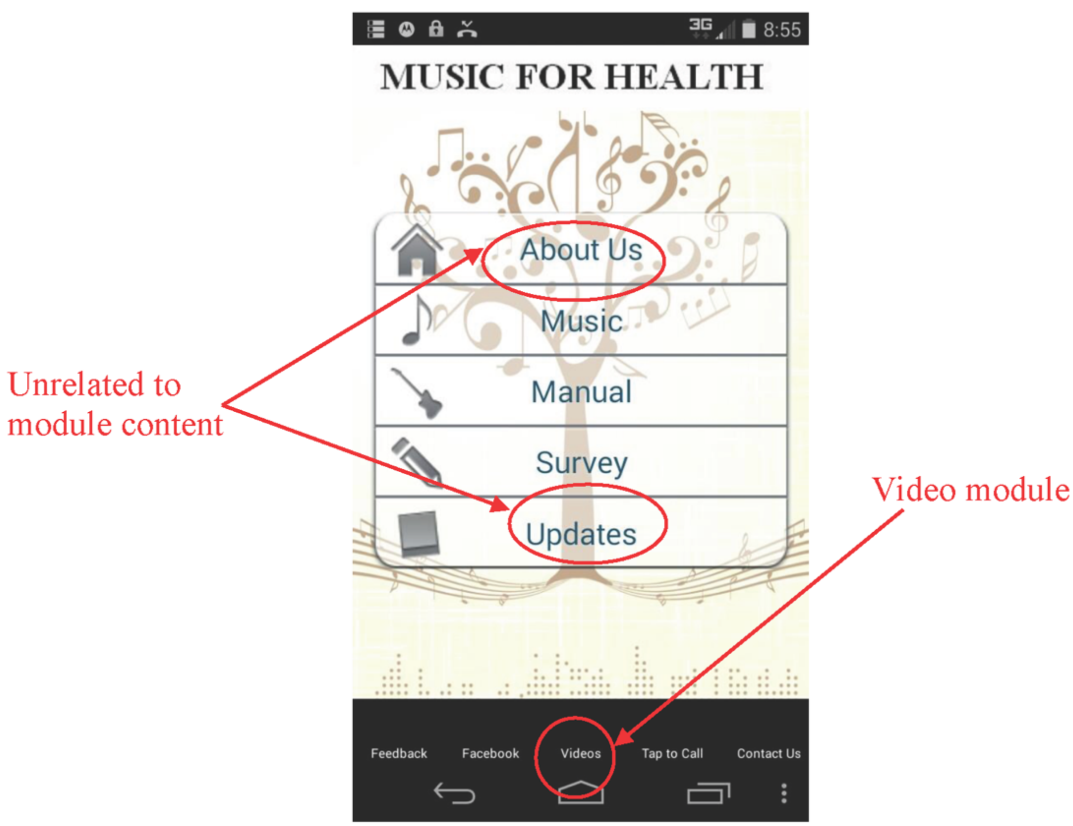
Potential Barriers to iApp Use

Frequency and extent of app usage were evaluated as primary outcomes, but this research did not examine why some individuals failed to access the iApp or used it much less than others – this is a question the MFHP parent study will explore. In the present study, reasons for the disparity between users and non-users can only be speculated. From a behavioral health standpoint, some participants may have avoided the app due to several well-established psychosocial barriers-to-care common among PLWHA living in the rural South: stigma, depression, lack of social support, and ineffective coping strategies (e.g., drug use, denial). All these barriers have been associated with suboptimal engagement in medical care, nonadherence to ART regimens and adverse health outcomes, such as rapid disease progression and higher mortality (Giordano, Hartman, Gifford, Backus, & Morgan, 2009; Kelly, Hartman, Graham, Kallen, & Giordano, 2014; Pellowski, 2013; Vyavaharkar et al., 2010).

Outside the context of health maintenance behaviors, technical and design factors could have contributed to decreased or no usage. The app shell was loaded onto each study phone to function as the user interface, and content was streamed over Verizon's LTE network or a wireless local area network via the iBuildApp centralized host site. Hence, the iApp relied on external connections for data delivery. Connectivity problems – incompatibility with iBuildApp system upgrades, signal interruptions, slow connection speeds, or network unavailability – might have hampered efforts to access the app. Furthermore, the interface itself may have been too unclear or complicated, both commonly cited causes of app disuse (Krebs & Duncan, 2015;

thinkwithGoogle, 2015). In this case, the menu layout could have confused some participants when attempting to access specific content, especially the videos. Figure 9 shows a screen shot of the main menu where the manual, music, and survey modules are centered in the screen with a large font. Two seldom used and possibly distracting elements unrelated to the intervention, “About Us” and “Updates”, are also prominently displayed in the center section, while the video module appears at the bottom of the screen in a much smaller font. Informal queries by study staff to participants about video use revealed that many either forgot about the video module or missed the link altogether because of its location and small size.

Figure 9. MFHP iApp Menu



UTAUT2 and iApp Use

Behavioral Intention and Its Antecedent Conditions

UTAUT2 survey scores indicated that all MFHP participants accepted the iApp with the intention to adopt, but the impact of certain antecedent conditions on overall technology acceptance substantially differed by age. Younger, technologically savvy people indicated mobile apps were easy to use and placed high importance on an app's innovation or entertainment value. Older individuals perceived mHealth apps as more difficult to use and were less inclined to adopt based on novelty. All age groups placed equal importance on an app's personal usefulness. These results were consistent with Slade, Williams, and Dwivedi's (2013) qualitative research on age-related mechanisms affecting mHealth acceptance. They reported that older focus group members expressed frustration when adapting to unfamiliar software and rapidly changing, innovative technology. This was especially true in presence of disability (e.g., deteriorating eyesight, poor manual dexterity) or inexperience operating smartphones. The parent study's eligibility criteria required no self-reported bilateral hearing loss; otherwise, physical disabilities, such as those previously mentioned, were not evaluated as possible impediments to mHealth acceptance and adoption. Older participants were also less experienced using smartphone technology, with many never owning a smartphone or having owned one for only a short time.

Behavioral Intention and iApp Usage

Rather than supporting the hypothesis that behavioral intention directly influences usage behaviors, iApp metrics demonstrated a disconnect between the two. Usage was low among all participants, but recently diagnosed individuals, most with high behavioral intention scores, had no or low recorded app openings. This almost paradoxical intention-behavior gap and its predisposing factors are not well described in the literature, conceivably because a large proportion of eHealth acceptance research uses behavioral intention as a proxy for behavior. In one of the few longitudinal studies examining the influence of intent upon behavior, Bhattacherjee and Sanford (2009) found that a strong, positive attitude towards a technology's potential personal/professional advantages narrowed the intention-behavior gap through moderation. The authors also posited that a desire to improve/maintain social standing (i.e., social desirability – expressing a strong intention to use technology to impress others but possessing a weak will to actualize) possibly plays a role in the mismatch between intention and behavior, but their results did not support that hypothesis. In the current study, the attitude toward personal advantage could be extrapolated as a correlate of performance expectancy; however, issues with the data (i.e., small sample size and poor variability in BI scores) precluded a post hoc analysis to measure moderation on the intention-behavior relationship. These problems, including that of social desirability bias, are addressed in the limitations section of this chapter.

Theoretical Rationale for iApp Non-Usage

Although conditions facilitating the wide intention-behavior gap cannot be explicated from the data, the UTAUT2 framework might still elucidate reasons for low iApp usage among participants. For example, marketing research indicates that the hedonic appeal (enjoyment factor) of an app often predicts its viability, mainly among younger users (Furner et al., 2014; thinkwithGoogle, 2015; Yardley, 2009). Successful apps incorporate dynamic features (e.g., periodically "pushing" new material) into the software and provide instant gratification through built-in feedback, such as progress trackers, or social media, a growing source of eHealth information and advice among youths and minorities (Chou, Hunt, Beckjord, Moser, & Hesse, 2009; E. Z. Kontos, Emmons, Puleo, & Viswanath, 2010; thinkwithGoogle, 2015). During the inception phase of the MFHP study, developers created the iApp to include all content at once, enabling users to explore any topic at any time. Feedback and social media components were not integrated into the app's design, and interactions outside of scheduled visits were limited to periodic text messaging with research staff. In this sample, newly diagnosed individuals, several of whom were in their twenties and thirties, may have abandoned the app early in the study after its initial appeal diminished.

Another crucial component of technology acceptance is that of performance expectancy, or the anticipated benefits derived from using a technology. In the current study, participants living with HIV for over a year, many aged 40 years or more, accessed and spent time in the iApp more regularly. This outcome reflects earlier findings in technology acceptance research indicating that with the expectation of tangible future gains (in this case, better health through more effective HIV self-management), older individuals are more willing to overcome initial learning curves to use new technologies (Peek et al., 2014; Smith, 2014; Tavares & Oliveira, 2016). As mentioned earlier in this chapter, recently diagnosed MFHP participants might be less interested in using an mHealth app to receive future (versus immediate) health benefits for lack of perceived need. They may feel less ill, have a better baseline health status, or experience a more acceptable quality of life than those who have lived with HIV for years or decades. This could explain no or low record of usage after the baseline visit.

Moderating Factors in the UTAUT2 Framework

Smartphone Experience

Years of smartphone ownership and educational status significantly correlated with self-reported proficiency using common smartphone features. Participants who owned their devices longer, possessed a postsecondary education, or were younger than age 37 scored highly on the smartphone experience scale. These individuals accessed of a broad array of smartphone features almost daily, especially the Internet, camera, music/video, and text functions. Older smartphone owners, typically late adopters who owned their devices for less than a year, text messaged and took pictures at least once a week, but they rarely or never used any of the other features. The patterns of use in this study correspond with other research examining the habits and practices of smartphone users in the United States (Smith, 2014, 2015)

eHealth Literacy

Most sociodemographic variables measured in this study were not associated with eHealth literacy except for African American race and younger age, both of which were associated with strong perceived eHealth literacy across the content areas identified by Norman and Skinner (2006a) and described in Chapter 3. Older participants with lower baseline eHealth literacy scores were less confident they knew which health resources were available online or how to use the Internet to locate these websites. They were also less certain how to use online health information. These findings were consistent with Tennant et al.'s (2015) and Manafò and Wong's (2012) reports that many older adults lack the confidence and/or the ability to find and evaluate Internet-based health information. Consequently, they risk harm by following health advice from inaccurate or outdated online health sources (Moat, Gauvin, & Lavis, 2014). Nonetheless, the older group did markedly improve perceived eHealth literacy in most domains at the three-month follow-up visit, while their younger peers' already high perceptions remained stable. According to C. D. Norman and Skinner (2006b), regular exposure to unfamiliar or seldom used technologies improves eHealth literacy over time. This might have been the case with older MFHP participants as they began to use their smartphone features, including the iApp, more regularly.

The overrepresentation of African Americans in the sample could have overstated the relationship between race and eHealth literacy, but the literature suggests that subjective experiences and perceived abilities seeking online health information differ along racial lines according to the type of eHealth resources utilized. In their respective analyses of sociodemographic trends in eHealth use, Chou et al. (2009) and Kontos et al. (2010) reported that young African Americans rely on social networking sites more than other ethnicities for health communications and advice. Other studies found that people from minority backgrounds almost exclusively depend on mobile broadband for Internet access to download health information, but not paid eHealth apps, onto portable devices (Djamasbi & Wilson, 2015; Krebs & Duncan, 2015; Smith, 2015). By comparison, Caucasians are more likely to employ personal computers when searching web-based health topics or accessing patient web portals (Calhoun et al., 2016; Fox, 2011; Gordon & Hornbrook, 2016).

Computer ownership was not evaluated at baseline, and it is unknown if participants had alternative access to Internet-based eHealth resources. Prior research suggests that household computer ownership and Internet use significantly decrease with older age, lower income, and rural residence (File & Ryan, 2014; Rainie, 2015; Smith, 2014). Based on these findings, there is a decreased likelihood that MFHP smartphone non-owners – the largest proportion of whom were older than age 50 – either owned a personal computer or regularly researched health topics via the Internet prior to admittance into the parent study. Hence, the low baseline eHealth literacy in this group mirrored the low information technology usage demonstrated among older individuals in the general population.

Smartphone Experience and eHealth Literacy as Moderators

As mentioned earlier, the data could not be used to examine moderating influences of eHealth literacy and preexisting smartphone experience on the relationship between behavioral intention and its antecedent conditions. This was disappointing because, to the author's knowledge, there is no extant literature examining these interactions within the context of technology acceptance theories. Although moderation was not tested using this sample, data from the larger parent study may yet shed light on the impact of eHealth literacy and baseline technology experience on mHealth acceptance and adoption.

Study Strengths

This study had several strengths. It was one of the first to examine theoretical precursors to the acceptance and adoption of an mHealth app among PLWHA living in a rural setting. MFHP researchers developed the smartphone-based iApp to improve medication adherence and disease self-management in this population. Guided by the UTAUT2 framework, this study measured the strength of iApp acceptance by identifying how participants' characteristics and perceived needs changed the relationship between behavioral intention and its antecedents.

This was also among the few longitudinal studies evaluating the influence of behavioral intention on objective measures of behavior. Most technology adoption research employs cross-sectional designs, often substituting behavioral intention for adoption behavior as the primary outcome. While helpful to provide a snapshot of differentiating characteristics between adopters and non-adopters, cross-sectional research cannot establish temporal associations in the intention-behavior relationship. This study expanded on previous work by examining the impact of subjective intentions on real-time metric iApp usage over time.

Finally, to the author's knowledge, this was the first study investigating the contribution of eHealth literacy to overall technology acceptance and adoption. Although that relationship could not be elucidated because of small sample size and data limitations outlined in the next section, this research raised awareness of eHealth literacy's potential role moderating relationships among constructs within any adoption/acceptance framework. This could be an important consideration during the development phase of an eHealth intervention targeting individuals with limited technology experience, but the true impact of eHealth literacy on overall technology adoption remains to be seen.

Study Limitations

This research was not without its limitations. First, the study was underpowered because of the small sample size. The original power analysis assumed that 75 participants would enter the study; however, the final sample was less than one-half of the projected numbers due to slow recruitment and enrollment in the parent study. One of the biggest impediments to recruitment at every site was the dependence on clinic staff, often a single designated liaison, to identify and speak to eligible patients about the study before allowing the MFHP site coordinators to initiate contact with them. These procedural steps, while required by participating clinics, placed an extra burden on already busy workloads and frequently resulted in delays finding interested recruits. Consequently, the reduced sample size rendered the study insufficiently powered to reliably detect effect sizes, as well as to perform logistic regression when evaluating moderating relationships.

Second, there was little variability in survey results because most respondents answered at or near the highest possible score on each of the UTAUT2 subscales at the baseline and three-month visits (i.e., a ceiling effect). One possible explanation is that the subscales, which were highly intercorrelated, acted as proxy measures of each other rather than measuring individual traits. This lack of dimensionality may have stemmed from a poor revision of the UTAUT2 survey, despite the author's attempts to preserve most of the source instrument's original wording. Alternatively, the consistently high survey scores could be attributed to social desirability bias, where survey respondents over-report what they believe are desirable behaviors/attitudes to be perceived in a more favorable light by the investigators. This type of response bias, most commonly seen in behavioral research, threatens the validity of the survey instrument. In retrospect, the revised UTAUT2 instrument should have been analyzed using a small test group to verify the preservation of each domain before final dissemination. Reverse wording some of the items might have mitigated response bias; however, there is no clear consensus on the efficacy of this approach.

Last, the Flurry metric data were zero-inflated, indicating overall low app utilization. While it is possible that participants simply did not open the iApp as expected, technical difficulties arose over the course of the study that might have resulted in underreported use. One of the main problems was the age of the smartphone, the 2012 Motorola DROID RAZR M, in conjunction with incompatible Android mobile operating system (OS) upgrades. This smartphone model became obsolete when it could not be upgraded to the latest Android OS version and when it stopped receiving technical support from Verizon in 2016. iBuildApp, which hosted the MFHP's apps, routinely upgrades its platform to stay current with the most recent Android OS versions, but with resultant compatibility issues manifesting in difficulties accessing the app (a resolved problem) and limited capture of participant data from Flurry. Flurry still detects smartphone use on an aggregate level but beginning in early 2016, inconsistently reports individuals' daily metric totals.

Taking the above limitations into account, alterations were made to the original analytical plan by changing the approach from parametric to non-parametric techniques. Compared to parametric statistics, non-parametric tests can be less efficient and less explanatory. Thus, this research was transformed from a predictive to a descriptive study that cannot be generalized outside the context of the larger MFHP study population.

Future Directions

Consistent with previous research, this study demonstrated strong associations between behavioral intention and its antecedent conditions; however, it also emphasized the gap between positive behavioral intention and its actualization. Reasons for this disconnect are ill-defined in the literature, and additional research is recommended to evaluate factors moderating the intention-behavior relationship using objective adoption measures as outcomes-of-interest. The moderating influence of eHealth literacy on all construct relationships within a theoretical acceptance/adoption model should also be further investigated.

Low usage early in the study was a key characteristic defining MFHP participants who had been living with HIV/AIDS for less than a year. Newly diagnosed PLWHA comprise a high-risk group for medication nonadherence and inadequate disease self-management; therefore, barriers and facilitators of mHealth app stickiness (MHAS) among these individuals should be more fully explored. Future mHealth interventions are recommended to include app components hypothesized to facilitate MHAS: social media, dynamic content, and instant feedback (e.g., progress trackers).

Last, this research highlighted the potential influence of perceived severity of illness and/or quality-of-life on the perceived need for an mHealth intervention to maintain or improve health. Neither have been investigated within the context of technology acceptance, especially among younger or newly diagnosed chronically ill individuals. To fully examine the impact of disease on eHealth acceptance/adoption, future studies should integrate a health-related quality of life instrument and a perceived severity of illness scale into their frameworks.

Implications

Research Implications

The current study raised awareness of the potential downside of making behavioral intention the primary outcome in an intervention underpinned by a technology acceptance framework. Technology acceptance research often relies on behavioral intention as a cost-effective, ostensibly accurate substitute for behavior; however, the results of this data analysis suggest that in the absence of factors moderating the intention-behavior relationship, behavioral intention alone could greatly overestimate actual usage. Ultimately, implementing intention as a proxy for behavior may lead to falsely optimistic conclusions about the efficacy of an intervention.

Clinical Implications

Newly diagnosed participants (i.e., less than a year) opened the app significantly fewer times than those who had been diagnosed over a year prior to entrance into the study. These findings suggest that a one-app-fits-all approach might not be the most efficient or effective way to improve disease self-management and medication adherence equally among all HIV-positive patients. Whereas more experienced PLWHA could be better positioned (and more willing) to reap the benefits of an mHealth app with either intermittent or no clinician contact built into its architecture, newer patients may require a more personalized mHealth intervention that includes frequent clinical feedback and emotional support to kick-start engagement-in-care. This is especially important when considering the physical and mental toll of depression, stigma and grieving that often accompany the initial HIV diagnosis.

Finally, before assigning an app as a treatment adjunct, the clinician should evaluate the patient's theoretical willingness *and* his/her behavioral readiness to use mHealth. This should include an inventory of baseline technology experience, an explanation of how mHealth works to supplement health care, and a discussion of common concerns (e.g., privacy, expense) related to mHealth use. By taking the time to understand each patient's technology needs and mHealth expectations, the provider can successfully promote mHealth uptake to improve disease self-management and medication adherence among individuals living with potentially debilitating chronic illnesses.

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Appendix A

Venkatesh Permission to Use UTAUT2

RE: Permission to use UTAUT2 scale for dissertation

Viswanath Venkatesh [vvenkatesh@vvenkatesh.us]
Sent: Thursday, December 11, 2014 12:05 PM
To: Baumann, Maya

Thanks for your interest. You have my permission.

You will find other related papers at: http://vvenkatesh.com/Downloads/Papers/fulltext/downloadpapers.htm

You may also find my book (that can be purchased for a significant student discount and faculty member discount) to be of use: http://vvenkatesh.com/book

Hope this helps.

Sincerely,
Viswanath Venkatesh
Distinguished Professor and George and Boyce Billingsley Chair in Information Systems
Walton College of Business
University of Arkansas
Fayetteville, AR 72701
Phone: 479-575-3869; Fax: 479-575-3689
Email: vvenkatesh@vvenkatesh.us
Website: http://vvenkatesh.com
IS Research Rankings Website: http://vvenkatesh.com/ISRanking

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From: Baumann, Maya [mailto:maya.g.baumann@emory.edu]
Sent: Wednesday, December 10, 2014 2:37 PM
To: vvenkatesh@vvenkatesh.us
Subject: Permission to use UTAUT2 scale for dissertation

Dear Dr. Venkatesh,

I am an Emory University doctoral student whose dissertation focuses on determinants of intention and usage of a smartphone-based medication adherence program. I am interested in examining these elements using the UTAUT2 scale because it includes hedonic motivation, in addition to the other UTAUT constructs. May I have your permission to employ this scale in my research?

Regards;

Maya Baumann

Maya Baumann, MSN, MPH
Doctoral student
Emory University
Nell Hodgson Woodruff School of Nursing
1520 Clifton Rd
Atlanta, GA 30322-4201
maya.g.baumann@emory.edu

Appendix B

Norman Permission to Use eHEALS

Re: Permission to use eHEALS scale in dissertation
Cameron D. Norman [cameron.norman@utoronto.ca]
Sent: Wednesday, December 10, 2014 3:53 PM
To: Baumann, Maya

Dear Maya,

You have my full permission to use the eHEALS. Best wishes with your research.

Cameron

Baumann, Maya wrote:

> Dear Dr. Norman;
>
> I am an Emory University doctoral student whose dissertation focuses on determinants of intention and usage of a smartphone-based medication adherence program. Because very little eHealth/HIT acceptance literature has examined the moderating effects of eHealth literacy on intent-to-use and subsequent usage of device-based interventions, I would like to include the eHEALS scale you developed as one of my measures. May I have your permission to do so?
>
> Regards;
>
> Maya Baumann
>
> Maya Baumann, MSN, MPH
> Doctoral student
> Emory University
> Nell Hodgson Woodruff School of Nursing
> 1520 Clifton Rd
> Atlanta, GA 30322-4201
> maya.g.baumann@emory.edu
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>
>

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Blog: http://censemaking.com

Appendix C

Venkatesh Permission to Modify UTAUT2

RE: Permission to use UTAUT2 scale for dissertation

Viswanath Venkatesh [vvenkatesh@vvenkatesh.us]
Sent: Saturday, January 24, 2015 8:59 PM
To: Baumann, Maya

Certainly.

Sorry for the delay, I have been traveling.

Sincerely,
Viswanath Venkatesh
Distinguished Professor and George and Boyce Billingsley Chair in Information Systems
Walton College of Business
University of Arkansas
Fayetteville, AR 72701
Phone: 479-575-3869; Fax: 479-575-3689
Email: vvenkatesh@vvenkatesh.us
Website: http://vvenkatesh.com

From: Baumann, Maya [mailto:maya.g.baumann@emory.edu]
Sent: Monday, January 5, 2015 11:21 AM
To: Viswanath Venkatesh
Subject: RE: Permission to use UTAUT2 scale for dissertation

Hi Dr. Venkatesh;

Sorry to bother you again; however, when I asked your permission to use the UTAUT2 scale, I neglected to ask if I could revise the scale's wording to reflect the purpose of my own study, which is centered on mHealth app usage. May I have your to do so?

Thanks again!

Maya

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Appendix D

UTAUT2 Survey

We would like to know your beliefs about smartphone applications (apps). Please select the the number for each of the following statements that best represents how you feel about using apps on a smartphone.

	Strongly Disagree (1)	(2)	(3)	Undecided (4)	(5)	(6)	Strongly Agree (7)
Performance Expectancy							
PE1: I find smartphone apps useful in my daily life	o	o	o	o	o	o	o
PE2: Using a smartphone app will help me achieve things that are important to me	o	o	o	o	o	o	o
PE3: Using a smartphone app will help me accomplish my goals more quickly	o	o	o	o	o	o	o
PE4: Using a smartphone app will help me stay healthy	o	o	o	o	o	o	o
Effort Expectancy							
EE1: Learning how to use a smartphone app is easy for me	o	o	o	o	o	o	o
EE2: Smartphone apps are clear and user-friendly	o	o	o	o	o	o	o
EE3: I find smartphone apps easy to use	o	o	o	o	o	o	o
EE4: It is easy for me to become skillful at using a smartphone app	o	o	o	o	o	o	o
Hedonic Motivation							
HM1: Using a smartphone app is fun	o	o	o	o	o	o	o
HM2: Using a smartphone app is enjoyable	o	o	o	o	o	o	o
HM3: Using a smartphone app is entertaining	o	o	o	o	o	o	o
Behavioral Intention							
BI1: I intend to use a smartphone app in the future	o	o	o	o	o	o	o
BI2: I will always try to use a smartphone app to manage my health	o	o	o	o	o	o	o
BI3: I plan to continue to use a smartphone app frequently	o	o	o	o	o	o	o

Appendix E

eHealth Literacy Scale (eHEALS)

We would like to ask you for your opinion and about your experience using the Internet for health information.
For each statement, indicate which response best reflects your opinion and experience *right now*.

	Not useful at all (1)	Not useful (2)	Unsure (3)	Useful (4)	Very useful (5)
Q1. How useful do you feel the Internet is in helping you in making decisions about your health?	o	o	o	o	o

	Not important at all (1)	Not important (2)	Unsure (3)	Important (4)	Very important (5)
Q2. How important is it for you to be able to access health resources on the Internet?	o	o	o	o	o

	Strongly Disagree (1)	(2)	(3)	(4)	Strongly Agree (5)
Q3. I know **what** health resources are available on the Internet	o	o	o	o	o
Q4. I know **where** to find helpful health resources on the Internet	o	o	o	o	o
Q5. I know **how** to find helpful resources on the Internet	o	o	o	o	o
Q6. I know **how to use** the Internet to answer my questions about health	o	o	o	o	o
Q7. I know how to **use the health information** I find on the Internet to help me	o	o	o	o	o
Q8. I have the skills I need to **evaluate** the health resources I find on the Internet	o	o	o	o	o
Q9. I can tell **high quality** from **low quality** health resources on the Internet	o	o	o	o	o
Q10. I feel **confident** in using information from the Internet to make health decisions	o	o	o	o	o

Appendix F

Smartphone Experience Questionnaire (SPexp)

	Yes	No	Don't know
1. Do you own a cell phone?	O	O	O
2. Is your cell phone a smartphone?	O	O	O
If yes, how long have you owned a smartphone? Please indicate time in days, months, or years.			
3. Have you ever owned a smartphone?	O	O	O
If yes, how long have you owned a smartphone? Please indicate time in days, months, or years.			
4. Have you had any experience using a smartphone?	O	O	O

We would like to learn more about your experiences using a smartphone. Using the scale below, estimate the number of times you have performed the following tasks on a smartphone in the past three months.

5. In the past three months, how often have you used a smartphone to	Never (1)	Less than once a week (2)	1-2 days a week (3)	3-6 days a week (4)	Every day (5)
5a) Send or receive email?	O	O	O	O	O
5b) Send or receive text messages?	O	O	O	O	O
5c) Send or receive picture messages?	O	O	O	O	O
5d) Send or receive video messages?	O	O	O	O	O
5e) Take pictures?	O	O	O	O	O
5e) Listen to music?	O	O	O	O	O
5f) Watch videos?	O	O	O	O	O
5g) Download and use apps?	O	O	O	O	O
5h) Access the Internet?	O	O	O	O	O
5i) Browse websites?	O	O	O	O	O