THE EFFECTS OF EXTERNAL CUES ON MEDIA HABIT AND USE: PUSH NOTIFICATION ALERTS AND MOBILE APPLICATION USAGE HABITS

By

Mijung Kim

A DISSERTATION

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Media and Information Studies – Doctor of Philosophy

2014

ABSTRACT

THE EFFECTS OF EXTERNAL CUES ON MEDIA HABIT AND USE: PUSH NOTIFICATION ALERTS AND MOBILE APPLICATION USAGE HABITS

By

Mijung Kim

This dissertation is an examination of how push notifications affect habit formation and the relationship between habit and mobile application use. For the purpose of this study, we created a simple weather forecast mobile application for a 20-day panel study of two randomly assigned groups: one received push notification alerts and the other did not. During the period of study, participants were asked to use the application every day and completed four surveys five days apart. This dissertation examined the temporal sequencing and mutual influence between habit strength for visiting the application and application usage behaviors (i.e., frequency of visits and duration on the application use) using bivariate latent difference score structural equation modeling. Longitudinal data from 115 smartphone application users revealed level of habit strength for visiting the application through push notification alerts to be positively associated with changes in frequency of visits. Higher scores on habit strength anticipated increases in frequency of visits. Repeated-measured ANOVAs showed a significant difference between users who received push notification alerts and the other users who did not in frequency of visits and push notification receivers visited the application more during the study period. In addition, users who clicked push notification alert messages visited more than users who received push notifications but did not click. These findings highlight the role of external media prompts in media habit formation and usage and provides evidence of causation in media use –

adding to our understanding of the cognitive mechanisms of media habit formation in ways that were absent in prior research.

This dissertation is dedicated to
my supportive parents, Jungsun Choi and Ginho Kim,
my love, Chonghoon Kim,
our precious daughter, Jiyu Kim,
and all my wonderful friends I met at Michigan State University
and Campus Mission Church at New York

ACKNOWLEDGEMENTS

Thanks to my advisor, Dr. Robert LaRose, I pushed myself to finish my Ph.D. I will always remember what you said, “Contribute to Science.”

Thanks to my committee, I improved my research.

Thanks to my parents, I finished my doctoral program.

Thanks to my love, CK, I was happy while writing my dissertation.

Thanks to my precious daughter, Jiyu, I learned how to manage time and energy.

Thanks to my friends, I survived the stress.

But without God, I couldn’t do anything.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

INTRODUCTION

Mobile phones are becoming so widely used that there are now 6.8 billion mobile subscribers worldwide (International Telecommunication Union, 2013). As mobile phones become popular as a media platform as well as a communication tool, recent design and technological improvements in mobile phones have been aimed at increasing the mobile phone's connectivity in order to facilitate immediate access for users (Soror, Steelman, & Limayem, 2012). Moreover, as the number of features and applications available on mobile phones increases, so do the kinds of activities people can carry out on them at any time and location.

Mobile technology continues to advance both in terms of the functionality of mobile devices and the quality of connections. The burgeoning choices of applications for data-enabled mobile phones (i.e., smartphones) are largely responsible for the expanded range of decision making processes these devices provide. A lot of this content is useful and enjoyable to users. Overall, mobile phone users experience fast and efficient information consumption and enhanced social networking. Notifications from push notification services transform smartphones into communication hubs that notify users of incoming information or events as people on the go engage with social networks, information services, location-based services, and interactive games.

Push notification services also allow "third-party application servers to actively send data to their installed applications, even when the installed application is currently not running" (Xu & Zhu, 2012, p. 11). To get push notification service, mobile application users are asked whether they want to receive notifications when they install applications. Through push notification services, mobile application providers can feed information to users in efficient ways and in a timely fashion. Notifications from push notification services serve as reminders leading people to ultimately use the installed mobile applications.

However, one of the most important concerns associated with mobile phone use is that it may become habitual, and eventually uncontrolled in ways that can impact our daily lives (Billieux, 2012; Soror et al., 2012). Nonstop information feeding by mobile applications also causes frequently repeated use by users without having conscious control over these behaviors. Many people answer their mobile phones without considering whether doing so interferes with more important ongoing tasks, such as driving a car (e.g., White, Eiser, & Harris, 2004). Dangerously, some people automatically respond to the push notifications on their mobile phones while driving and, accordingly, several states in the US as well as Washington D.C., Guam and the U.S. Virgin Islands, have banned mobile phone use while driving (Governors Highway Safety Association, 2013). Text messaging while driving has also been prohibited in 39 US states. There are other uncontrolled consequences of mobile phone use. They have infiltrated classrooms and threatened to undermine schools' authority and control over students by disrupting learning in a classroom setting (Campbell, 2005; Geser, 2004). Frequently a social nuisance, people also use their mobile phones in public places where their use can be distracting, at work meetings, in movie theaters and restaurants, and otherwise in places and situations in which their use is not considered appropriate (Turkle, 2008). In this respect, how push notifications are used can influence mobile phone usage behavior and its usage habits.

Regarding media use, studies found that habit was a significant and strong predictor (see LaRose & Eastin, 2004 for the Internet; Soror et al., 2012; Peters, 2007, 2009 for mobile phone use; Lee & LaRose, 2007 for video games). In particular, LaRose and colleagues used self-regulation mechanisms to explain habitual media use (see LaRose, 2010; LaRose & Eastin, 2004; LaRose, Lin & Eastin, 2003), which was defined as a form of automaticity in media use that develops as people repeat media consumption (LaRose, 2010). Specifically, self-regulation mechanisms (i.e., self-control and self-monitoring) are deficient when media use is habitual.

When dealing with the relationship between media use and media habits, the inevitable "chicken and egg" question raises its head: Which comes first? One train of thought is that as people use media repeatedly and spend more and more time using it, they eventually lose self-control over managing their media use. Alternatively, it is also thought that people spend more time on media *because* they cannot control their behavior. The third and perhaps most likely possibility is that the causal relationship is reciprocal. The relevance of this study is both based on this classic conundrum, and also because previous researchers could not identify the causal direction of the relationship since their studies were purely based on cross-sectional data (see Tokunaga & Rains, 2010).

Regarding the factors influencing habits, researchers argue that habitual behaviors are elicited by internal cues (e.g., mood states and motivations) (see LaRose & Eastin, 2004; Lee & LaRose, 2007; Peters, 2007, 2009; Soror et al., 2012) external cues or both (e.g., people, events, locations, etc.) (see Ouellette & Wood, 1998; Wood, Tam, &Witt, 2005; Verplanken & Wood, 2006). However, how features of media providing external cues influence media habit and media use has received scant attention. In mobile application use, the affordances of media devices, especially the notification function, may provide these powerful external cues, thereby influencing media usage habits. In other words, notifications from push notification services provide the cues that may trigger people to use their corresponding applications. In effect, people sometimes use their mobile phones in a way that is a counter to the users' intentions but as a habitual behavior, an automatic impulse to check push notifications. Furthermore, media technology design and artifact studies have focused on improving the external triggers, but they have paid little attention to their effects on actual user behavior (Barkhuus & Dey, 2003).

Because of these tendencies, and the fact that push notifications are the obvious affordance of interactive media that comes from the environment rather than directly from the person, push notification service was examined vis-à-vis users and non-users in this dissertation. The push notifications involved sending notifications, including potentially useful or interesting information in the form of messages that were shown on a mobile phone screen. In this dissertation, tests were run to see if push notifications had an effect on forming the habit of application usage. Push notifications for smartphones included initial information that could ignite internal cues, like curiosity or motivation. Thus, this dissertation will help us to more fully understand how push notifications influence users' controllability in mobile application use in terms of habitual behavior and the relationship between habit strength and mobile application use.

This dissertation begins with a review of existing literature addressing mobile phone use, including smartphones and automatic/uncontrolled mobile phone use. Then, this dissertation contains some conceptual groundwork and definitions of habit. The discussion of habit in media use is based on a theoretical framework by LaRose and his colleagues (LaRose & Eastin, 2004; LaRose et al., 2003; LaRose, Mestro, & Eastin, 2001). The present work focuses on the role of external cues provided by mobile devices in habit development and activation and the effect on the relationship between habit and the mobile application use.

LITERATURE REVIEW

This dissertation investigates the relationship between push notifications and habit formation with the aim of better understanding the causal direction of mobile application usage behavior. As a basis for understanding such behavior, this review considers literature dealing with the use of mobile phones and smartphones, including mobile phone use that is automatic or uncontrolled.

Mobile Phone and Smartphone Use

Mobile phones have become an indispensable medium for socializing and working (Takao, Takahashi, & Kitamura, 2009) as well as entertainment (Wei, 2008). As mobile technology has advanced, mobile phones' functions have expanded beyond calling and texting. Common uses now include exploring the Internet, managing emails, playing video games, purchasing products, watching videos, and working on documents. Data-enabled "smart" functions are not only common to mobile devices such as smartphones, but subscribers are using them at a high rate. Among mobile subscribers in the US, there was a 61% penetration rate of smart phones in 2013 (Nielsen, 2013).

Previous studies have approached the wide range of factors influencing mobile phone usage behaviors using a diverse array of theoretical frameworks and perspectives. Among them are Uses and Gratifications (U&Gs), Technology Acceptance Model (TAM)/ Unified Theory of Acceptance and Use of Technology (UTAUT), the effect of individual differences, and media habit based on Social Cognitive Theory (SCT). These studies provide a sense of how one's intentions affects mobile phone use, and conversely, how habit explains mobile phone use.

Further, some studies have specifically explored people's behavior vis-à-vis push notifications such as SMS in mobile phones.

Uses and Gratifications (U&Gs). U&Gs proposes that people are goal-directed in their media selection and usage; they actively choose a certain medium to satisfy their needs (Li, 2007; Park, Lee, & Cheong, 2008; Rubin, 2002). Previous U&Gs studies on media have consistently found that people are motivated to use communication technologies and other media and that their motivations play a critical role in influencing their actual use (Park et al., 2008). The common motives for using mobile phones are: social interaction, entertainment, immediate access, mobility, and fashion/status (Leung & Wei, 2000; Ozcan & Kogak, 2003; Peters & Allouch, 2005; Wei & Lo, 2006). Though researchers have targeted overall mobile phone use in several studies, some have also identified the motives for using specific functions and mobile technologies. For instance, the motives for using Short Message Service (SMS) via mobile phones were social interaction, immediate access, entertainment, and time-efficiency (Peters, Almekinders, Van Buuren, Snippers & Wessels, 2003). However, the motives found from the latter results are similar to those for overall mobile phone use.

Even though the defined motives of mobile phone use from U&Gs based studies reflect new ways in which users interact through mobile technology, the specific results of factor analyses of motivations and gratifications are inconsistent. Moreover, the variance explained by internal motives of mobile phone use among these studies using the U&Gs perspective was less than 20%, indicating that U&Gs do not fully account for mobile phone usage.

Technology Acceptance Model (TAM) and Related Models. A second perspective used to explain mobile phone use is TAM. According to TAM, an individual's behavioral intention to use a medium is determined by two beliefs: perceived usefulness (PU) and perceived ease of use (PEU) (Davis, 1989; Venkatesh & Davis, 2000). However, researchers have incorporated certain additional variables into TAM to account for the lack of social factors and consideration of other factors that could influence PU and PEU. In mobile phone research, for instance, ease of use and anxiety about using a new medium (apprehensiveness) predicted both extrinsic and intrinsic motivations of using mobile phone. Additionally, motivations as well as social pressure predicted worked-related mobile phone use (i.e., the number of calls) (Kwon & Chidambaram, 2000). In research focusing on wireless application protocol (WAP) -enabled mobile phone use, attitude and social norms positively related to behavioral intentions, whereas behavioral-control factors such as self-efficacy, mobile operator's facilitation (i.e., increasing the awareness of WAP-enabled mobile phones among users), and government actions (i.e., educating and facilitating new technology) had no effect on behavioral intentions (Teo & Pok, 2003). Regarding research on smartphone use, technical barriers negatively predicted behavioral control and behavioral control and social norms positively predicted both perceived enjoyment and perceived usefulness for mobile Internet service users. Both perceived enjoyment and perceived usefulness positively predicted usage intentions for advanced mobile service users (Verkasalo, Lopez-Nicolas, Molina-Castillo, & Bouwman, 2010). On the other hand, device characteristics and user characteristics positively predicted PU and PEU but design did not predict PEU (Kang, Cho, & Lee, 2011). However, those studies using TAM approaches include inconsistent additional factors to explain mobile phone use.

Venkatesh, Morris, Davis, and Davis (2003) formulated the Unified Theory of Acceptance and Use of Technology (UTAUT) to overcome the shortcomings of TAM by integrating main competing user acceptance models including the following: The theory of reasoned action (Fishbein & Ajzen, 1975), the technology acceptance model (Davis, 1989), the motivational model (Davis, Bagozzi, & Warshaw, 1992), the theory of planned behavior (Ajzen, 1991), a model combining the technology acceptance model and the theory of planned behavior (Taylor & Todd, 1995), the model of PC utilization (Thompson, Higgins, & Howell, 1994), the diffusion of innovations paradigm (Rogers, 1995), and social cognitive theory (Bandura, 1986). The UTAUT model includes four core determinants of technology adoption and use: (1), performance expectancy, (2), effort expectancy, (3) social influence, and (4), facilitating conditions. Research using UTAUT explored mobile phone adoption and use. The studies consistently found that performance expectancy, effort expectancy, and social influence explained mobile phone usage intentions, while facilitating conditions did not (see Carlsson, Carlsson, Hyvonen, Puhakainen, & Walden, 2006; Park, Yang, & Lehto, 2007)

Meanwhile, TAM and UTAUT researchers argued for the influence of past experience and habit in technology use as well. Prior experience of using similar technology was found to be a significant factor. In particular, past experience with similar technology predicted PEU of a new one (Agarwal & Prasad, 1996; 1999) and behavioral intention was strongly related to actual information technology use for those who had prior experience with similar technology compared to inexperienced users (Taylor & Todd, 1995). Furthermore, smartphone acceptance research showed that adopters are more likely to have use intention when they believe the technology is reliable and have confidence that the technology would be secure (Ally & Gardiner, 2012). The findings of Ally and Gardiner (2012) also supported the argument that prior experience is an important factor in technology use since belief in functions of technology is based on their experience, especially with a long-term and sustained interaction with the technology in question (Kim, 2012).

Regarding what leads to actual technology usage behaviors, the assumption of TAM is that technology use is determined by continuance intentions (Kim, 2012). However frequently performed past behaviors were likely to become habitual (Kim, 2012; Quellette & Wood, 1998; Wood, Quinn, & Kashy, 2002). In this respect, the effects of habits on actual media usage were tested in various studies. In particular, habit ($\beta = .53$, $p < .001$) was a stronger predictor of actual use than continuance intention ($\beta = .11$, $p < .05$) for mobile data services and applications (Kim, 2012).

UTAUT2 extended TAM and UTAUT by focusing on the consumer context including (1) habit, which is defined as an automatic behavior; (2) hedonic motivations, which are conceptualized as perceived enjoyment; and (3) price value, which is "consumers' cognitive tradeoff between the perceived benefits of the applications and the monetary cost for using them" (Venkatesh et al., 2012, p. 161). In the context of mobile Internet technology use, the UTAUT model explained additional variance in comparison to UTAUT, UTAUT2 ($R^2 = .44$ for behavioral intention and .35 for usage behavior, respectively). It was superior to UTAUT ($R^2 = .35$ of behavioral intention and .26 of usage behavior, respectively). Moreover, the findings of Venkatesh et al. (2012) demonstrated a strong effect of habit on mobile technology use. Hedonic motivations and price value positively predicted behavioral intension and habit directly and positively predicted both behavioral intentions and use of mobile Internet technology. The standardized path coefficient of habit ($\beta = .32$) was larger than the conventional UTAUT variables ($\beta = .21$ for performance expectancy, $\beta = .16$ for effort expectancy, $\beta = .14$ for social influence, and $\beta = .15$ for facilitating conditions, respectively) and new variables in UTAUT2 ($\beta = .23$ for hedonic motivations and $\beta = .14$ for price value, respectively) also predicted behavioral intentions.

Individual Differences. Other research focused on relationships among individual differences and mobile phone use. Major individual difference factors include personality traits. Correlations between the "Big Five" personality traits (i.e., extroversion, agreeableness, conscientiousness, neuroticism, and openness to experience) and mobile phone use were tested in various studies (e.g., Bianchi & Phillips, 2005; Butt & Phillips, 2007; Chittaranjan, Blom, & Gatica-Perez, 2011). The common findings from those studies showed that extroversion was positively related to spending more time on calling and texting whereas neuroticism was not.

Other individual difference variables such as age, self-esteem, and loneliness were found to be significant predictors of uncontrolled mobile phone use (i.e., problematic mobile phone use). For example, problematic mobile phone use was a function of age, extroversion, and low self-esteem (Bianchi & Phillips, 2005). Age was negatively related to problematic mobile phone usage whereas extraversion and low self-esteem positively predicted problematic use (Bianchi & Phillips, 2005). Gender, self-monitoring (i.e., extroversion, acting, and directness), and approval motivation (i.e., need for favorable evaluation from others) were significant positive predictors of problematic mobile phone use (Takao et al., 2009). Loneliness did not predict problematic mobile phone use, but it was related to overall mobile phone use. Overall, in problematic mobile phone use studies, habit was the strong predictor: loneliness, need for cognition, arousal, and habit positively predicted mobile phone "addiction," defined in terms of negative life outcomes and guilt, and habit was a stronger predictor than loneliness (Park. 2005).

Media Habits under Social Cognitive Theory. A third approach to explore mobile phone use is based on self-regulative mechanism from SCT (Bandura, 2001). SCT was adapted to explain media consumption by combining both conscious and non-conscious determinants of media usage behavior (see LaRose, 2010; LaRose & Eastin, 2004; LaRose et al., 2003).

According to SCT, self-regulation describes the role of self-direction and forethought as humans engage in long-range planning in pursuit of their goals. They do so through the sub-mechanisms of self-observation, the judgmental process, and self-reaction (Bandura, 2001). Self-observation is the process of monitoring one's own behavior to provide diagnostic information about its impact. These observations are then compared with relevant personal, social, or collective standards through the judgmental process (LaRose, 2010). Behaviors that are observed and judged to be inconsistent with those standards may be modified through self-reaction (control) by applying self-generated rewards or punishments, as well as by responding to one's self-evaluations.

LaRose et al. (2001) extended self-regulation to situations in which self-observation and self-control are ineffective in explaining the effect of habit on media use. Deficient self-regulation is defined as the state in which the self-regulatory process becomes impaired and self-control over media use is diminished (LaRose & Eastin, 2004). In the state of deficient self-regulation, self-observation is deficient when individuals act without awareness of the expected outcomes of their media-use behavior (LaRose, 2010).

In the context of mobile phone use, habit as a state of deficient self-regulation was a significant and a stronger predictor of ongoing mobile phone use than expected outcomes (Peters, 2009) and deficient self-regulation related to loneliness and anxiety influenced mobile phone use (Soror et al., 2012). Specifically, deficient self-observation predicted making a phone call and sending Short Message Service (SMS) messages (Peters, 2009). The frequency of habitual checking of a smartphone increased the overall amount of smartphone application use (Oulasvirta, Rattenbury, Ma, & Raita, 2011).

What some call “media addictions” are habits with deficient self-reaction, which may cause negative life outcomes (LaRose, 2013 in press). Scholars have argued that “addictions can be habits (Graybiel, 2008; Marlatt, Baer, Donovan, & Kivlahan, 1988), but not all habits are pathological addictions.” (LaRose, 2013, p. 20). Moreover, it is hard to find pathological cases of media use among the normal populations from the previous media addiction studies. LaRose (2013) found through a re-analysis of published data that interactive media induce low to moderate levels of deficient self-regulation in surveys of problematic use among of normal populations (e.g., Caplan, 2002). LaRose also argued that operational measures of addiction parallel those of deficient self-regulation (LaRose, 2013). Compulsivity in the media addiction literature is interchangeable with deficient self-reaction, which indicates lack of controllability in automatic behavior (i.e., habits). Losing track of time spent on media use, tolerance and withdrawal in the addiction literature are interchangeable with deficient self-observation (LaRose, 2013). In this sense, mobile phone use in inappropriate situations while driving, in class, or during a meeting certainly qualifies as a “bad” habit that annoys others and subjects users to social and physical risks.

Included in this dissertation are different perspectives related to mobile phone use. Two of them are seen in U&Gs studies, which focused on motivations for using mobile phones, and TAM, which tested PU and PEU as determinants of mobile phone use. Included here is also a discussion of UTAUT and UTAUT2, which are the extended versions of TAM. UTAUT2 seemed to have stronger power in terms of the amount of variance explained. Habit was the strongest predictor of mobile technology use as well as behavioral intentions. The SCT approach employing a dual process model focused on deficient self-regulation mechanisms and examined how habits work in media use. Table 1 lists different approaches of mobile phone usage behavior and reports the variance explained by each model from the previous studies reviewed above.

Previous studies including habits as a variable showed more variance explained and demonstrated that habit was a stronger predictor of media use than other motivational and social factors, or individual differences (see Table 1). For this reason, this dissertation centers on the effect of habit in mobile application use. The next section deals with definitions of habits and the process of habit formation.

Table 1

Different Approaches of Mobile Phone Usage Behaviors

Theoretical Approaches	Authors	Independent Variable(s)	Dependent Variable(s)	R^2 (R^2 Change)
U&Gs	Leung and Wei (2000)[1]	Gratification sought in cellular phone use (e.g., Fashion/Status, Affection/Sociability, Relaxation, Mobility, *Immediate Access*)	The number of calls made and received on a typical day	(.07)
	Ozcan and Kogak, (2003)[1]	Uses and gratifications (e.g., *Status/Relaxation*, Instrumentality/Business, *Security/Sociability*)	Total number of calls made to and received from friends, family members and business associates during the last week	(.09)
	Peters and Allouch (2005)[2]	Mobile PDA use gratifications (e.g., Permanent access, Entertainment, Social interaction, Attraction, Connection, Instrumentality, Fashion/Status)	PDA use over time	
	Peters et al. (2003)[1]	SMS motives (e.g., *Entertainment*, *Social Interaction*, *Immediate Access*, Efficiency in time)	Total number of SMS-messages sent in a week	.14
	Wei and Lo (2006)[1]	Cell-Phone Gratifications (e.g., Information-seeking, *Social utility*, *Affection*, *Fashion-status*, Mobility, *Accessibility*)	a) Frequency of family-calls made, b) Frequency of social-calls made, c) Frequency of family-calls received, d) Frequency of social-calls received	.09, .10, .101, and 103, respectively
	Wei (2008)	Mobile phone use motivations (e.g., Pass time, Sociability, Reassurance, Instrumentality, *Communication facilitation*) and Mobile phone use in general (e.g., *Voice calling via mobile phone* and *Use of add-on telecomm. Services*)	Use of mobile phone a) for News-seeking, b) for Surfing the Web, and c) for Playing games	11.5, 17.6 and 9.4, respectively
TAM	Kim (2008)	*Perceived Cost Savings, PU, PEU, Company's willingness to fund*, *Job relevance*, *Experience*, *Behavioral intention to use a smartphone*	Actual use of a smartphone	.07
	Kwon and Chidambaram (2000)[3]	PEU, *PU* (i.e., extrinsic motivations), *Enjoyment/fun* (i.e., intrinsic motivations), *Social pressure*	a) Number of calls, b) Length of calls, c) Personal use, d) Work-related use	.02, .02, .02, and .04, respectively

Table 1 (cont'd)

TAM	Teo and Pok (2003)	*Attitude, Subjective norm*, perceived behavioral control, *relative advantage*, perceived ease of use, *Image, Compatibility, Risk, Significant others, Self-efficacy*, Government, Mobile operator	Behavioral Intention to adopt WAP-enabled mobile phone a) for using news group/forum and b) for email	.587 and .425, respectively[4]
	Verkasalo et al. (2010)	*Technical barriers, Behavioral control, Social norm, Perceived enjoyment, PU*	Intention to use smartphone application	.35[5]
	Kang et al. (2011)[6]	*Wireless Internet, Design, Multimedia, Application, After service, PU, PEU*	Behavioral intention to use smartphone	
UTAUT	Carlsson et al. (2006)[7]	Performance expectancy, Effort expectancy, Social influence, Facilitating conditions, Mobile device/service anxiety, *Attitude*	Behavioral intention to use mobile service	
	Park et al. (2007)[8]	*Performance expectation, Effort Expectation, Social influence*, Facilitating condition, *Attitude*	Intention to use mobile technology	
UTAUT2	Venkatesh et al. (2012)	*Performance expectancy, Effort expectancy, Social influence, Facilitating conditions, Hedonic motivation, Price value, Habit*	Behavioral intention	.44
	Ally and Gardiner (2012)[9]	Perceived usefulness, Perceived ease of use, Hedonic motivation, Price value, Habit, Facilitating conditions, Trust, Perceived security, Social influence, Attitude	Behavioral Intention	
	Kim (2012)	*PU, Confirmation, Perceived enjoyment, Perceived monetary value, User satisfaction, Habit, Variety of Use, Continuance intention*	Actual usage of mobile data service and application	.36
Individual Differences	Bianchi and Phillips (2005)	*Self-esteem, Extraversion, Neuroticism*	a) Time spent on mobile phone during the week, b) The number of people called regularly using the mobile phone, c) Mobile phone problematic use scale, d) Social use of the mobile phone, e) Business use of the mobile phone, f) SMS use, and g) Use of mobile phone that is related to other features	.22, .09, .40, .11, .11, .33, and .05 respectively

Table 1 (cont'd)

Individual Differences	Butt and Phillips (2008)	Neuroticism, *Extraversion*, *Agreeableness*, Conscientiousness, Self-esteem	a) Average time spent making and receiving calls, b) Amount of incoming calls, c) Amount of unwanted incoming calls, d) Average time spent writing and receiving SMS, e) Average time spent changing ring tone and/or wallpaper	.12, .16, .12, .24, and .17 respectively
	Chittaranjan, Blom, and Gatica-Perez (2011)[10]	*Extraversion, Agreeableness, Conscientiousness, Emotional Stability, Openness to experience*	a) Uses of Office, b) Uses of Internet, c) Uses of YouTube, d) Use of SMS, e) Incoming calls	.12, .09, .58, .07, and.07, respectively
Media habits based on SCT	Peters (2009)	Experience, Self-efficacy, Expected outcomes, Habit Strength, Deficient self-regulation	Mobile phone usage	.67
	Soror et al. (2012)	*Boredom*, Anxiety, *Deficient self-regulation*, *Habit*	Mobile phone use	.35

Note. Independent variables in italics significantly predicted one or more dependent variables in each study ($p < .05$). [1]The studies included other independent variables such as social structural variables (e.g., gender, age, education), past experience, place of use, or mobile service operator. However, this table only included the reported R^2 or R^2 change of the effect of gratifications on mobile phone use. [2]The study found seven different motivations to use PDA and tested the strength of motivations on PDA use over time. The result of Friedman Chi-square test showed means of all the motivations changed over time. Specifically, the means of entertainment and fashion/status motivations increased, whereas those of rest of motivations decreased. [3]The study included other dependent variables such as personal use and work-related use. However, this table only included number of calls and length of calls operationalized as cell phone use in other studies. [4] The value is η^2. [5]This result is the model for smartphone users. [6]Model fit index of structural equation model, CFI = .88, TLI = .86, RMSEA = .08. [7]Model fit index of structural equation model, CFI= .92, GFI = .91, RMSEA = .061. [8]Model fit index of structural equation model, CFI = .92, GFI = .91, RMSEA = .06. [9]The study is an abstract of research. [10]The study included more dependent variables (i.e., 40 different smartphone features). This table included the main features that had significant results.

Acquiring Media Habits

Although the debate continues over how habits should be conceptualized and operationalized (LaRose, 2010; 2013), scholars generally agree that “habits are acquired through incremental strengthening of the association between a situation (cue) and a behavior” (Lally et al., 2010, p. 998). Furthermore, researchers have suggested the automaticity with which a behavior is performed when the cue is encountered is the key characteristic of habitual behaviors. Verplanken and Melkevik (2008) defined habit as a form of automaticity in responding that develops as a person repeats a particular behavior in stable contexts. Wood and Neal (2007) stated that “habits are sub-served by a form of automaticity that involves the direct association between a context and a response but that interfaces with goals during learning and performance” (p. 843). Habit has three central aspects: (a) repetition of behavior, (b) automaticity of behavior, and (c) contextual cues (Verplanken, 2006; Wood & Neal, 2007). Habit can be characterized as a form of automaticity that involves the association of a cue and a response (Hull, 1943; Lally, Jaarsveld, Potts, & Wardle, 2010; Ouellette & Wood, 1998).

Current perspectives of habits identify themselves as examples of automaticity (Verplanken & Orbell, 2003; LaRose, 2010). A dual process model supports this perspective. When people first decide to perform a certain behavior, they might go through a phase in which the behavior has to be carefully planned and incorporated into existing routines. During this phase, the decision to perform the behavior is likely to be made consciously and deliberately. However, once the behavior has been satisfactorily established as part of the individual’s everyday routine, the behavior in this phase is carried out repeatedly without necessarily forming a conscious intention to perform it. Such behavior is characterized by a lack of awareness and mental efficiency, and, possibly, difficulty in controlling the behavior. This is called a habit.

Such an automatic and routinized activity involves a restructuring of cognitive tasks with more efficient cognitive algorithms (Saling & Phillips, 2007). In other words, as a frequently repeated and automatic behavior, a habit achieves cognitive efficiency by protecting individuals from being overwhelmed when processing information related to routine activities (LaRose, 2010; Limayem et al., 2007; Verplanken & Melkevik, 2008). Whereas new or infrequent behavior requires mental effort and conscious thinking, less energy is required—in terms of mental effort and conscious thinking—when a behavior is continually repeated. Automaticity in a behavior can be detected in people using some or all of the following features: mental efficiency, lack of awareness, lack of conscious intention, and difficulty controlling the behavior (Bargh, 1994; Bargh & Ferguson, 2000). By defining habit as a form of automaticity, one can understand how uncontrolled less conscious behavior is executed.

Then, what is the role of cues in habits? When looking at how habits are formed, one can understand how scholars defined habits as behaviors that are cued. Neuroscientists explain habits by stimuli-response (S-R)/reinforcement theory. That is, “all behavior is elicited by some antecedent stimuli from the external environment, and that the consequence of behavior, by providing satisfaction or dissatisfaction to the organism, merely reinforces or weakens the S-R association” (Yin & Knowlton, 2006, p. 465). The consistent conclusion of neurological research on habits is that instrumental behaviors are controlled by either the goal-directed (action-outcome) system or the S-R system, where goal-directed actions are shifted to S-R habits by the function of the basal ganglia (Ashby, Turner, & Horvitz, 2010; Yin & Knowlton, 2006). Hull (1943) stated that habit strength reflects the extent to which a behavior was reinforced in the past. In this sense, habit formation is a function of repetition when reinforcements are received for performing the behavior upon encountering a cue (Lally et al., 2010). Research has shown that behavior becomes habitual when it is over-trained and over-learned (i.e., degrading the contingency between an action and reward has no effect on performance). Thus, one can perform an action not to earn rewards but as a response to external stimuli (LaRose, 2010; Yin & Knowlton, 2006). In this case, immediate reinforcement is no longer needed as long-run average outcome expectations take over immediate reinforcement (LaRose, 2010).

Concerning factors that influence habit formation, there are debates over the effect of goals and internal cues versus those of external cues. Some scholars focused on the effect of internal cues on habit and argued that habitual media use is goal or motive-directed rather than externally cue-directed (e.g., Neal, Wood, Wu, & Kurlander, 2011). Their argument is that goals are the driving force in the initial stage of habit formation as people repeat particular actions to fulfill their expected outcomes (Neal et al., 2011). In this sense, media use may be initially thought of as an active, controlled process under the conscious control of the user (LaRose, 2010). As time passes with repetition of media use, there are opportunities for active, volitional behaviors to become automated to free up mental resources for other tasks (LaRose, 2010; LaRose et al., 2003). As a result, initial goals, such as the gratifications that individuals initially seek when sampling new media content, lose their influencing power on habitual behaviors (Triandis, 1979) and behaviors are cued by recurring contextual cues (Neal et al., 2011; Limayem et al., 2007; Verplanken & Wood, 2006). Hence, the term "force of habit," as if appearing externally or automatically, may be aptly titled.

However, the operationalization of habit was inconsistent. One party operationalized habit as the frequency of past behavior rather than the automaticity of behavior (Ouellette and Wood, 1998). However, using frequency of past behavior for habit measures was criticized by other scholars who argued that frequently repeated behaviors could have been controlled by conscious goals on each repetition (Ajzen, 2002; LaRose, 2010). Moreover, the findings studying frequency of past behavior could not provide clear evidence of automaticity in behaviors. Habit strength did not have a linear relationship with frequency of behavior performance; rather, it displayed an asymptotic curve (Lally et al., 2010). The findings indicated that habit strength was unlikely to further increase after it was formed (Verplanken et al., 2005; Yin & Knowlton, 2006). This finding violated the assumption that frequency of past behavior indicates habit strength. In this respect, recent scholars have focused on automaticity in habitual behaviors.

Regarding the factors evoking habitual behaviors, some empirical studies have shown that both internal states, such as goals, motives, or mood, and external cues (e.g., physical location, time, or people) influenced habitual behaviors. Mood has been found to be related to habitual fast food purchases, watching television news, and riding the bus. For these three habits, the external cues of physical location, time, and people are related (Ji & Wood, 2007). External events or situations (i.e., attending a lecture, taking a bus trip, and being at home) and internal states (i.e., expected outcomes such as killing time) are related to smartphone usage habits (Oulasvirta et al. 2011). Another study examined an eating behavior (i.e., popcorn eating) and found that the habit was not related to current motivational states (e.g., hunger) but was performed rigidly in the recurring context associated with frequent past consumption (i.e., a movie theater) (Neal et al., 2011).

However, there are relatively fewer studies on the effect of external cues than those focusing on internal cues, especially regarding media use. Specifically, in mobile phone use, the notification function may provide these external cues. This dissertation tests how external cues (in this case, push notifications) influence habit and media use. The next section addresses the role of external cues in habits and discusses their effects in media use.

Effects of External Cues on Media Habits

Little has been said regarding how media features with external cues may influence the formation of habit connected to media use. Media technology design and artifact studies have focused on improving external triggers (Barkhuus & Dey, 2003) and many researchers have studied the role of external cues in habits. Scholars have argued that external cues that elicit specific responses form habits (Guinea & Markus, 2009; Markus, 2005; Markus & Silver, 2008; Wood & Neal, 2007; Verplanken & Wood, 2006) in that a conditioned response where the stimulus is provided by the environment and the responses always follow relatively immediately upon the presentation or incidence of the stimulus (Watson, 1919, p.10).

According to Fogg's (2009a) behavioral model, not only habits but also all behaviors need three factors to be performed: (1) sufficient motivation, (2) sufficient ability, and (3) effective trigger. Fogg emphasizes that people should have these all three factors at the same instant to perform a behavior. In habitual behaviors, people already and fully have the first two factors; for them, the role of the third factor, triggers, is critical. According to his behavior model, the trigger, defined as "something that tells people to perform a behavior now" (p. 5) must be present to occur with sufficient motivation and sufficient ability to perform a target behavior (Fogg, 2009). Fogg (2009a) specified three types of triggers: (1) spark, (2) facilitator, and (3) signal. A spark is a type of trigger that can leverage motivational elements such as pleasure, hope, or social acceptance. The second type of trigger is a facilitator, which can make people with high motivation and no ability perform a target behavior. A facilitator tells people the target behavior is easy to do. The last type of trigger is a signal. This trigger works as a reminder; thus, it works best for people with relatively high motivation and the ability to perform a target behavior.

Wood and Neal (2007) asserted that "context cues refer broadly to the many elements of the performance environment that potentially can recur as actions are repeated, including physical locations, other people, and preceding actions in a sequence" (p. 845). Thus, external cues can directly activate a previously learned performance, especially overlearned, habitual behavior. Regarding the role of external cues in habit acquisition and performance, Wood and Neal (2007) suggested two types of cuing: direct cuing and motivated cuing. Direct cuing emerges from simple, direct context-response associations that develop from repeated co-activation of the context and response. Thus, when directly cued, habits are represented in memory (Wood & Neal, 2007), where "direct cuing involves the cognitive neural changes that result from repeated co-activation of responses and context" (p. 845). This direct cuing can be found in classical conditioning. In Pavlov's (1927) experiments, after the repeated association with a ringing bell and food, the ringing bell became a conditional stimulus that caused the dog to salivate. As classical conditioning shows, habit is consistently activated in conjunction with representation of a context (e.g., hearing a bell ringing), and the association between the habit and the context is gradually formed through repetition (Wood & Neal, 2007).

Motivated cuing emerges from the value of the rewarding experiences associated with past contexts and responses (Wood & Neal, 2007). The external cues are contiguous with a rewarded response and the reward value becomes conditioned onto the cues. As in direct cuing, sufficient repetition between the cues and the rewarded response is required in order for the habit to be formed. As a result, the cues themselves have the power to motivate the response because they signal an opportunity to acquire the associated reward (Neal, Wood, & Quinn, 2006; Wood & Neal, 2007). Therefore, direct cuing and motivational cuing are related to each other rather than mutually exclusive since it is possible that motivational cuing can enhance the cue-response association within direct cuing (Wood & Neal, 2007).

Fogg's three types of triggers and Wood and Neal's direct vs. motivating cues share the idea that external cues are a critical booster to make people perform a target behavior by by reminding them it is time to perform it. More importantly, when the association between cues and a target behavior is developed, the target behavior becomes an automatic response to the cue and motivation and ability are no longer relevant. Habits of eating, drinking or exercising behavior could be formed in response to a salient cue (e.g., the next activity in a habitual morning routine after one finishes breakfast) as an automatic response to the cue (Lally et al., 2010).

However, unlike other habitual behaviors, such as exercising, eating, smoking, or drinking (e.g., Lally et al., 2012), there are only few studies testing the effect of external context cues on habitual media use and their findings are conflicting compared to other behavioral domains. Specifically, in those studies external context cues were conceptualized as context stability focusing on the interruption or instability of a setting. For example, Newell (2003) examined the effect of environmental stability as a contextual cue on the habit of media choice with Verplanken and Orbell's (2003) Self Reported Habit Index (SRHI), which measures automaticity and ability of behavior control. Newell's (2003) study borrowed Ouellette and Wood's (1998) concept of the stability of the environment by focusing on the interruption or the instability of a setting rather than specific elements of environmental influence on habitual behavior. "Tonight was a typical weeknight for me" was the only indicator of stability. Habit was correlated to media choice but there was no moderating effect of stability. When the contexts of newspaper and television viewing habits were disrupted, the effect of context stability was more significant for those who had weak habits than strong habits in media use (Wood, Tam, & Witt, 2005). However, Ajzen's (2002) analysis revisited the findings of Ouelette and Wood (1998) concerning the role of context stability for the habit of television viewing. Consistent with Newell (2003), the difference in the correlation of past behavior to future behavior between consistent contexts and inconsistent contexts was not statistically significant. Overall, the effect of external cues on media habits still remains a question since there are few empirical studies testing it and previous findings are conflicting in part because of inconsistent operationalization of habit and external cues, and unreliable self-reported measures of contextual cues. Also, media habits were not solely reliant on context stability for their performance; rather, they "may be elicited by a wider range of stimuli (LaRose, 2010, p. 206)".

To date, the existing literature has not addressed the potentially powerful role that external media prompts may have in guiding media users to respond to their devices. In essence, such prompts, as stimuli, may affect conditioned responses unless users make serious usage errors or the technology fails (Guinea & Markus, 2009). Like those contained in stabile real world environments environment, external media prompts given by media technologies (e.g., sounds, notifications or visual cues) are direct cues for the performance of a consistent activity just prior to usage behavior. As technology develops, scholars have focused on the effects of interactive technologies on people's attitudes and behavior changes. Specifically, they have suggested the role of external media prompts in various situations such as learning, shopping, and media using. For instance, especially in social media use, Fogg (2009b) speculated that repeated and continued behaviors cued by Facebook use include users' poking back friends, reading others' posts, joining an event, responding to friend's post, and sending birthday messages. Fogg speculated that Facebook users developed certain usage habits through responding and associating cues and the behaviors. In this sense, this dissertation proposes that push notifications in smartphone applications can be the salient external cues that stimulate media use and activate media habits..

The next section will provide explanation of what push notifications and how it works in forming habits of smartphone use.

Push Notifications and Habits of Media Use

Push notification service is a popular functionality provided by almost all data-enabled mobile phone platforms, especially smartphones. The mobile applications, which send push notifications, are usually Internet-based and use the push technology to actively send information to the users who install the applications, even when the installed application is currently not running (Edmunds & Morris, 2000; Xu & Zhu, 2012). To send a notification, the sending application first prepares a notification object and registers a trigger event for it. Mostly, trigger events include information updates. When the trigger event occurs, the notification fires. Depending upon the user profile or handling function defined in the installed application, the pushed data may or may not be displayed directly on the screen (Xu & Zhu, 2012; Zakaria, 2003).

In use of mobile phone for texting and calling, push notifications have been found to be used in decision making process by users because push notifications provide the initial information about the sender of text messages or calling. Research found that people first determine who is calling them or sending text message to them before responding, especially in inappropriate situations such as while driving (Walsh, White, Hyde, and Watson, 2008). In other research regarding mobile phone use in the workplace, people first check the sender of text messages, evaluate the importance of him or her in their relationship, and then decide whether to ignore the messages or respond to them (Fischer et al., 2010; Grandihi & Jones, 2010).

Then, how are push notifications, as external media prompts, related to mobile application usage behaviors? In particular, when considering the fact that use of mobile technology (i.e., mobile phone use and mobile data service and application use) was found as a habit (e.g., Peters, 2007; Soror et al., 2012; Venkatesh et al., 2012), how do push notifications influence habit formation and habitual usage behavior of mobile applications?

Compared to other external cues such as location or time, push notifications might more directly influence the shift from a goal-directed action to an uncontrolled, habitual one. As the application continues sending push notifications and the user repeatedly responds and uses the application, the notifications initiate application usage behavior, the launching of the application, and cause automatic behavior as a result of repeated association: push notifications precede the launching of the application. The process of habit formation through push notifications is the shift from goal-directed actions to S-R habit. Goal-directed action is involved as users launch the application through clicking the first notifications they receive to get new information, which is the initial goal of using the application, while the new information works as the reward. However, as this application usage behavior is performed repeatedly in response to notifications, the users automatically respond to the notifications even when they are not in appropriate situations, such as while driving or attending a meeting, or when the information has not immediate reward value, showing S-R habit. After the application usage habit forms, the action is not goal-directed anymore and the initial goal of using the application is long forgotten. Also, the reward becomes no longer effective. This indicates that automatic response to push notifications would precede automatic application visiting behavior. Then, are push notifications as media prompt salient and active cues to lead growth in habit strength and in turn, lead application use? Based on this discussion, this dissertation proposes the following hypotheses.

> **H1a:** Users who receive push notifications from a mobile application will have higher levels of habit strength for overall mobile application visitation than those who do not receive notifications.
> **H1b:** Users who receive push notifications from a mobile application will visit the application more frequently than those who do not receive push notifications.

Relationship between Habits and Media Use

In testing the relationship between habit and media use, there are two approaches (Tokunaga & Rains, 2010). The first approach suggests that underlying psychological problems make people use media and that the amount of time spent using media causes the habit. The logic is that the deeper the psychological problems that individuals have, the less they can regulate their behavior (e.g., Chou & Hsiao, 2000; Young, 1998). The second perspective suggests that habits influence one's behavior; the less ability audiences have to control their behavior, the more they use media (e.g., LaRose & Eastin, 2004; LaRose et al., 2003; Soror et al., 2010).

For the former approach just mentioned, researchers characterize uncontrolled and problematic media use as a clinical pathology (e.g., Chou & Hsiao, 2000; Hur, 2006; Jenaro et al., 2007; Koo, 2010; Young, 1998) and conceptualize uncontrolled media use as a psychological dependence marked by the increased investment in media usage activities (Tokunaga & Rains, 2010). This pathological approach suggests psychosocial problems as antecedent to the relationship between habit and media use. That is, psychosocial problems may contribute to people spending more time using media and later becoming unable to control behavior. In this respect, this approach proposes that individuals use media more and more to mitigate or cope with the ill effects of their psychosocial problems, such as social anxiety, loneliness and depression, which can lead to uncontrolled media use. Therefore, uncontrolled media use may require clinical or professional intervention to remedy the problem called “media addiction” (Young, 1999; Tokunaga &Rains, 2010).

Arguing that media addiction cannot be applied to all uncontrolled media use, LaRose and his colleagues consider uncontrolled media use as a marker of deficient self-regulation (LaRose, 2010; LaRose & Eastin, 2004; LaRose et al, 2003). The rationale for viewing uncontrolled mobile phone use differently from other behavioral addictions, such as problem gambling, is that it can be hard to pinpoint uncontrolled media use since almost everyone has a mobile phone and uses it regularly. It would be difficult to find cases where people experienced serious negative life outcomes among normal populations due to uncontrolled and excessive mobile phone use, such as, say, losing a job, a marriage, or a position in school. LaRose et al. (2003) recognized deficient self-regulation as both habitual and impulsive behaviors, one of the main characteristics of which is loss of control. This perspective proposes that the loss of self-control or insufficient self-regulation results in increased media consumption. Thus, from this perspective, psychosocial problems impair successful self-regulation associated with media use and uncontrolled media use results in increased time spent on media consumption through the formation of habits (LaRose et al., 2003; Schaeffer, Hall, & Vander Bilt, 2000; Tokunaga & Rains, 2010).

To test this relationship between habit and media use in the context of problematic Internet use (PIU), Tokunaga and Rains (2010) conducted two path analyses using weighted mean correlations among the variables (i.e., habit[1], time on the Internet, and psychosocial

---

[1] Tokunaga and Rains (2010) operationalized PIU as failure to control Internet use, withdrawal symptoms, and substitution of face-to-face social interaction, so this dissertation refers to failure to control as habit.

problems) derived from meta-analysis. The habit model, the latter model, was supported but the pathology model was not. This indicates that habit can explain media use. But their data still had serious limitations. Since the analyses of Tokunaga and Rains (2010) were based on the cross-sectional data, their results cannot conclusively demonstrate the direction of the causal relationship between habits and media use. Tokunaga (2013) used a time series analysis similar to the present dissertation but examined general Internet use rather than the role of push notification cues.

Researchers have used the deficient self-regulation approach to test the relationship between habit and mobile phone use. Peters (2009) found that deficient self-regulation, deficient self-observation[2] in particular, predicted making a phone call and sending Short Message Service (SMS) messages. Soror et al. (2012) also found deficient self-regulation affected mobile phone use. Habitual checking on a smartphone increased the use of a smartphone application (Oulasvirta et al., 2011). In Billieux's (2012) pathways of problematic mobile phone use, a lack of control influenced mobile phone use.

The third possibility of the causal direction between habit and media use is reciprocal causation. For instance, when people feel lonely or depressed, they use media such as Internet or mobile phones (Caplan, 2002, 2003; Davis, 2001) and their self-regulation ability may become deficient (Soror et al., 2012). This deficient self-regulation increases time spent on media causing negative consequences in their lives, and in turn, exacerbates psychosocial problems. And again, to compound the effect, increased time spent on media inhibits self-regulation ability.

[2] In the original articles by Peters (2009), the authors referred to deficient self-observation as habit strength.

A fourth possibility in the causal direction between habit and media use is that both the pathological approach and deficient self-regulation approach are correct and that the direction depends upon the phase of habit formation (LaRose, 2013). The process of habit formation is described as shifting from goal-directed actions to S-R habits. If we focus on the shifting process causing severe negative life consequences, the pathological approach may be able to explain more variance in the relationship between habit and media use. The pathological approach suggests that increased media use causes media habits, which indicates that the goal-directed media use (i.e., to escape from reality or to get social support) becomes automatic and uncontrolled through repetitive media use. If we are interested in continually excessive media use and how S-R "habit" works in such an ongoing scenario, the deficient self-regulation approach may provide a clear explanation for the causal direction between habit and media use. The assertion with the deficient self-regulation approach is that different levels of habit strength lead to different levels of media use for those where the habit is preexisting. The important emphasis of this approach allows researchers more insight into the mechanics of habits, or, to understand better how habits "work" as well as how they are formed.

Unlike actions such as running a mile every day or drinking water after breakfast (Lally et al., 2012), there is no specific study to show the causal relationship between habit and media use. Previous studies are based on cross-sectional survey data, which does not validly establish the direction of the causal relationship between them. Although media use seems to involve repetitive behavior (e.g., watching television and surfing the Internet), the contents the users consume dynamically and constantly change. Therefore, there has been debate about whether habit causes media use or vice versa. Based on the argument of the relationship between habit and media use, this dissertation proposes the following hypotheses.

H2a: Habit strength for mobile application visitation will positively predict the frequency of mobile application visits.

H2b: Overall habit strength for mobile application visitation will positively predict the duration of visits to the mobile application.

To fully understand the above-mentioned association, it is worth considering how media use was conceptualized in previous studies. Those focusing on mobile phone use, used frequency as a measure of media use (e.g., Peters, 2009; Soror et al., 2012). Perhaps, differences in the physical settings of Internet use, mainly with desktop versus mobile phone use along with what content users seek from each medium, influence the patterns of media usage behaviors. Although media habits predicted both duration and frequency and accumulated frequent visits might contribute to longer durations in media use, no research exist that examines the hidden differences between duration and frequency. In this respect, the following research question is proposed to explore the association between frequency and duration in media use.

RQ1: Will frequency of application visits positively predict the average duration of application visits on mobile applications?

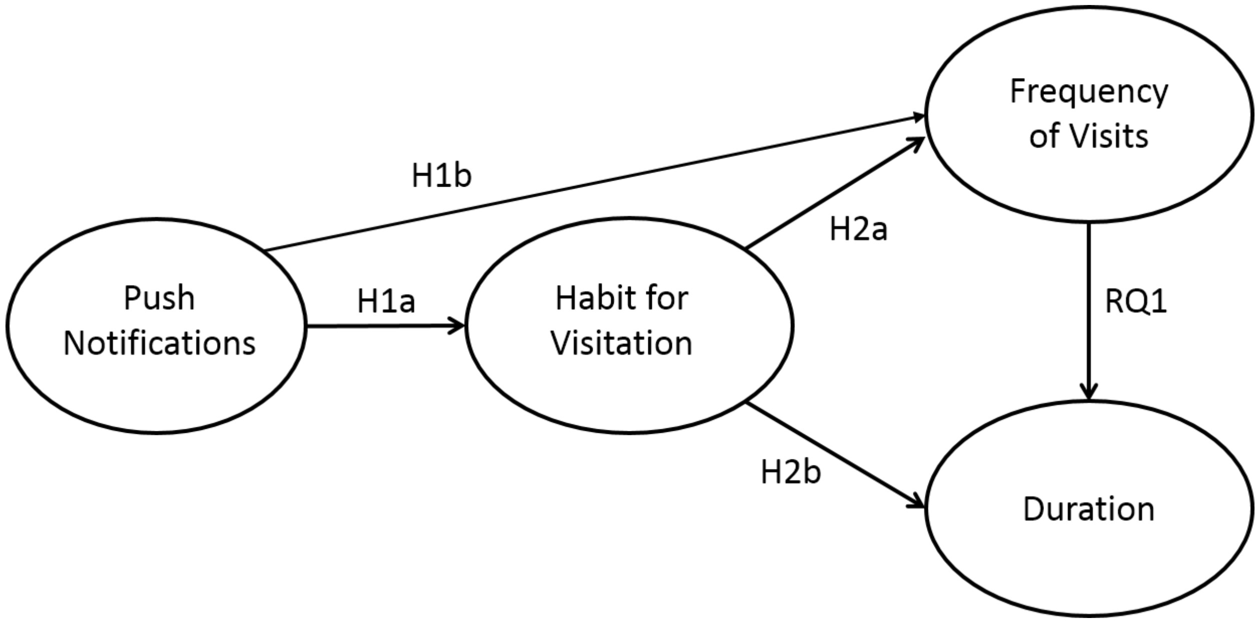


Figure 1. Proposed model for associations among push notifications, habit for visiting through push notification, habit for overall visitation, frequency of visits, and duration of application visit.

METHOD

The aim of this dissertation is to investigate how push notification alerts influence mobile application habits and application use as well as the causal direction of the relationship between habit strength and application use.

Research Design and Instrumentation

To explore how external media prompts (push notifications) influence habit formation and application visiting behavior as well as duration using the application, a weather forecast application was developed for this dissertation. The application, *Weather Story*, provided current weather information such as temperature, humidity, weather condition (e.g., sunny, cloudy, rainy, or snowy), and a three-hour weather forecast on the front page. On the second page, it provided a three-day weather forecast including highest temperature, humidity, and overall weather conditions. The weather information was sourced through the free website, Weather Underground (www.wundergroud.com). *Weather Story* was developed for smartphones running either iOS and could be installed on any version of the iOS system (iOS 3, 4, 5, or 6) as well as the Android operating system supported by all versions from 2.2 through 4.0.1. See Figure 2 and 3 for depictions of the *Weather Story*.

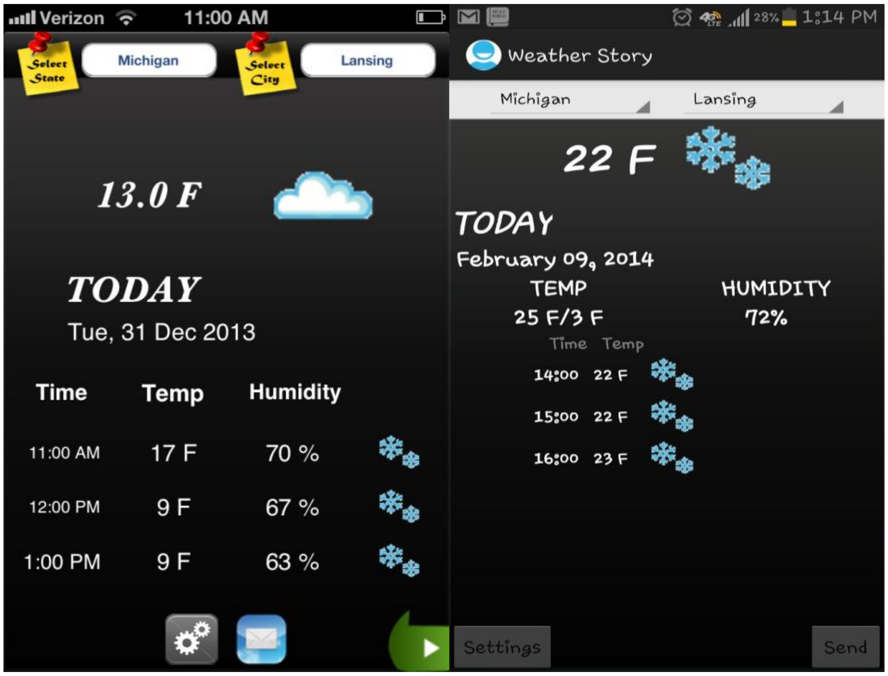


Figure 2. Depiction of the *Weather Story* application's front page on iPhone (left) and Android phone (right)

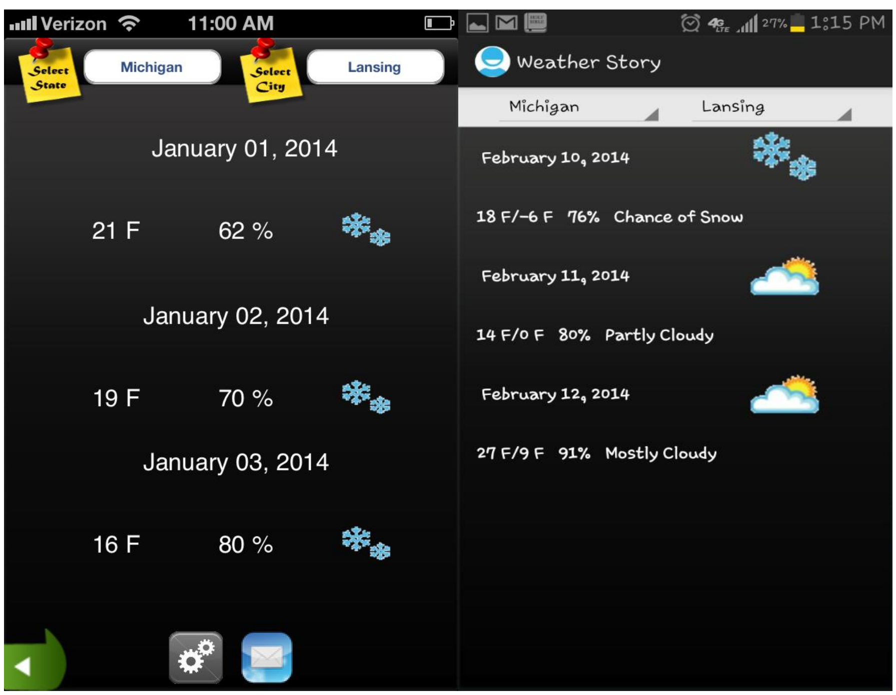


Figure 3. Depiction of the *Weather Story* application's second page on iPhone (left) and Android phone (right)

To test the effects of push notifications on habits and application usage behaviors, two different versions of *Weather Story* were developed: one provided push notifications by sending notification alerts and the other did not. Concomitantly, this study involved two groups: (1), the push group receiving notification alerts from *Weather Story*, and (2), the non-push group not receiving alerts. Participants were randomly assigned to either group.

To examine the relationship between habit strength and application usage behaviors, habit strength and behaviors were measured for 20 days. Prior research found that people developed new habits and strengths of the habits stabilized at a constant level around 20 days after starting doing the actions (Lally et al., 2010).

During the training session, participants were informed that the researcher was interested in users' experience in mobile application and they were asked to use Weather Story for 20 days and complete four surveys throughout their participation in this study to get $20 incentive. Both push group and non-push group were instructed how to install and use *Weather Story* on their smartphones in the training session led by the researcher. The push group was asked to enable the push notification function on their phone settings and shown how the push notifications would work by the researcher. All participants were asked to use *Weather Story* rather than any other weather applications during the study.

This dissertation combined time and event cues in the form of external cues generated by a smartphone. Participants in the push group received notification alerts at different times between 9 a.m. and 9 p.m. based on weather changes of the day. To avoid the occurrence that the push group might not get any push notification in a day, the author designed the application to send a push notification at 9 a.m. every day. Besides the push notifications delivered at 9 a.m., weather updates provided an uncongenial situation in which to establish habits according to previous thinking about habit formation stressing context stability. Specifically, push notification alerts were sent based on the weather changes rather than specific time since time cues are readily available and don't require careful smartphone monitoring to identify when to act, facilitate the automaticity associated with habitual behaviors that are repeatedly enacted at the same time each day (Lally et al., 2010). Indeed, an influential operational definition of habits (Wood et al., 2002) defined them in terms of actions that occurred at the same time each day. However, unexpected specific situations (i.e., changes in the weather) can also evoke automatic, uncontrolled actions if they are consistently associated with external cues (i.e., smartphone notifications) (Lally et al., 2010, p. 999).

During the 20-day course of the study, a total of 77 push notification alerts were sent to the push group. The average number of notifications sent was 2.57 (*SD* = .63) with a range of 1 to 4 push notification alerts per day. The push group received an external time cue notification saying "Check Today's Weather" every morning at 9 a.m. (Figure 4). When there was a temperature change of five degrees Fahrenheit or more, or when the chance of rain or snow reached 90%, the application sent a push notification alert to all participants. In these cases, the alerts read, "Temperature has changed. Please check it out!" and "It's about to rain/snow. Please check it out!" (Figure 5).

Push notifications required an action before proceeding (i.e., launch or close the application). Push group participants were able to launch the *Weather Story* application and see the front page by clicking through the "launch" button in the push notification alerts they received or clicking the "close" button if they did not want to open the application. Push notification alerts were also designed to disappear from the screen when participants pushed the home button of their devices (for iPhone users) or touch screen (for Android users). Push notification alerts were also visible in the lock screen. The application is designed to launch after unlocking the screen thus leading the participants to the front page of the application. As an alternative method to open the application, both push and non-push group participants were able to launch the application by clicking the *Weather Story* application icon on their devices. See Figure 4 and Figure 5 for a depiction of push notification alerts sent from *Weather Story*.

Figure 4. Depiction of push notification delivered at 9 a.m.

Figure 5. Depiction of push notifications in the lock screen

Figure 6. Depiction of push notifications for temperature change notification

To collect accurate behavioral usage data, *Weather Story* was designed to send usage log data automatically from each participant's device to the researcher's email. The log data included the username that each participant created for this study, frequency of visits, log-in and log-out times, the time that push notifications were sent, and the time of responses to the notifications during the five days.

Usernames were used to match survey responses to usage data from the log data. Upon installing *Weather Story*, participants were prompted to use the username they created in the beginning of the study and to keep the same username for the survey. After entering the username, they could select the location. All participants were located in Lansing, Michigan during the period of the study.

Participants

The researcher obtained a random sample of 24,000 domestic undergraduate students from the registrar's office at a major Midwestern university. The study was advertised to these students through an email invitation saying that only smartphone users could participate in the

20-day study. From the invitation email, the students were informed that this study was to test mobile application usage behaviors and they needed to complete five surveys including a pretest questionnaire (See Appendix B). Interested participants were first asked to make an appointment for an individual initial meeting to install the application that the researcher developed for this study. However, the response rates to the invitation email were less than 5% and only 135 students participated in the study. More participants were recruited from classes at the university. The researcher physically visited those classes and explained the study. In addition, the researcher asked instructors of the classes to send online invitations. Additional participants (37.3%) were recruited from several large communication classes with the same invitation message. In exchange for participating in the 20-day study, there was a $20 payment offered. The incentive for the participants was not contingent on behavior change or habit development.

At the initial meeting, participants were welcomed and briefed on the purpose of this study and requirements of the study (i.e., smartphone users, agreement to install new mobile application and complete several surveys). Those who agreed to participate in the study were randomly assigned to one of the groups and were asked to complete a short questionnaire regarding their smartphone ownership, experiences using mobile weather applications, interest in and familiarity with using any weather forecast application, and their habit strength for any weather application. After completing the pretest questionnaire, participants learned how to install the application and the researcher showed the configuration of the application and explained how to use it. For the push group, the researcher showed an example of push notifications and what would happen when the “launch” button or “close” button was clicked.

Those participants who had little interest in using a weather application and low familiarity were excluded (a score lower than 3 on a 7-point scale, 1 = Not at all and 7 = Very much). Those who had high level of habit for any weather application use were included in this dissertation since research finds that current habits (i.e., habit strength for using mobile phone) predicted adoption of a similar technology (i.e., mobile video phone) (Peters, 2007). This dissertation developed a weather forecast application similar to popular ones such as Weather Channel and Weather Bug.

Every five days, participants received an online survey request link via email. Hence, a total of four online survey links were emailed to the participants during the course of the 20-day study. Participants were also informed that their application usage data, including the number of visits and duration of using the application, would be exported automatically from their devices to the researcher's email. On the 20th day of the application trial, the participants received an email requesting their mailing address to receive a $20 paycheck as compensation. The 20-day study period, during which participants were asked to use the application, began March 20th 2013 and ended April 8th 2013.

A total of 214 enrolled students came to the initial meeting and 166 students actually used the application and completed at least one survey. For all participants who installed the application in Wave 1, the completion rate was 71 %. Over 89% of these participants were retained in the sample from wave to wave. However, the researcher found a technical problem in sending log files. The log files were supposed to be sent automatically from participants' devices to the researcher's email account, but some log files were not sent. Because of this problem some cases were excluded as incomplete data. There was one outlier in the duration variable (2827 seconds at Time1) from the non-push group and this case was also excluded. After attrition, the present data analysis is based on the 115 students who completed surveys and whose application log files were successfully delivered at all four waves of data collection. Data was used for 63 participants in the group receiving push notifications and for 52 in the group not receiving push notifications. In comparing those who dropped out of the study by Wave 4 or those who were excluded from the data with those in the original sample, the former showed no differences with respect to either their familiarity ($F = .42$, $p > .05$) or interest ($F = .07$, $p > .05$) using a weather application or past experience ($F = .35$, $p > .05$). Gender ($r = -.13p > .05$), race ($r = .08$, $p > .05$), age ($r = -.02$, $p > .05$), length of the current smartphone use ($r = -.08p > .05$), and the type of OS ($r = .03$, $p > .05$) were not correlated with dropping out of the sample.

Measurement

Pretest questionnaire. ***Familiarity and interest in using weather forecast mobile applications.*** Participants' familiarity and interest in using weather forecast mobile applications were considered since they might influence the level of involvement using this study's application. Familiarity and interest were measured by participants' agreement ratings on a 7-point scale (1 = Not at all; 7 = Very much). The questions are read as: "Are you familiar with mobile weather forecast applications?" ($M = 5.36$, SD = 1.29), and "Are you interested in using a mobile weather forecast application?" ($M = 5.79$, SD = 1.10).

Prior experience using weather forecast mobile applications. Prior experience using any type of weather forecast mobile application by the participants was addressed using a dichotomous question (i.e., yes/no). As with other habit strength measures used in this study, prior mobile application usage habit strength was measured using four question items borrowed from Soror et al.'s (2012) study and slightly modified for the purpose (i.e., changing the term "checking cellphone" to "using a weather application") of rating participants' levels of agreement on an 11-point scale (1 = strongly disagree; 11 = strongly agree). The question items are as follows: (1) "Using a weather application has become a habit for me," (2), "I don't even think twice before using a weather application," (3), "Using a weather application is part of my usual routine," and (4), "I use weather application without really thinking about it." (*M* = 7.91, *SD* = 2.11, *α* = .84)

Main Questionnaire. ***Frequency and duration of application visits.*** The two dependent measurements in this dissertation, the frequency and duration of application visits, were measured by averaging the number of application visits per day and averaging the time spent per visit (in seconds) using the differences between log-in and log-out times per visit across each 5-day reporting period.

Log-in times were determined as the time when the application was opened on users' smartphone screen and log-out times were determined as the time when the application disappeared from the screen (i.e., when users closed the application, powered off their smartphones, or switched to other applications).

Habit strength for frequency of visits. In this study, habit strength is defined as the extent to which people tend to perform a behavior automatically. In relation to the application in this study, habit strength was determined using four items borrowed from Soror et al.'s (2012) study and modified for the purpose of this study (i.e., changing the term "checking cellphone" to "using *Weather Story*"). Participants rated their level of agreement on an 11-point scale (1 = strongly disagree; 11 = strongly agree). The question items are as follows: (1) "Using *Weather Story* has become a habit for me," (2) "I don't even think twice before using *Weather Story*," (3) "Using *Weather Story* is part of my usual routine," and (4) "I use *Weather Story* without really thinking about it." Specifically, application use was implied frequency of visits.

Table 2

Fit Indices from the Confirmatory Factor Analysis and Cronbach's Alpha Reliabilities of Repeated Habit Strength Measures

	M	SD	α	χ^2	p	CFI	RMSEA	SRMR
Prior experience using weather forecast mobile applications (N = 94 including participants who had previous experience of using a weather application)								
Pretest	6.86	3.53	.80	.629	.43	1.00	.00	.011
Overall habit strength for frequency of visits (N = 115 including push and non-push groups)								
Time1	5.99	2.01	.85	.225	.64	1.00	.00	.007
Time2	6.29	2.29	.94	.639	.42	1.00	.00	.003
Time3	6.29	2.66	.97	.043	.84	1.00	.00	.001
Time4	6.62	2.74	.98	.172	.68	1.00	.00	.001

Note. In some instances, the proposed model did not fit the data well. The modifications were made for the model for both scales: error terms for item 1 and 3 were correlated to each other. CFI = comparative fit index; RMSEA = root mean square error of approximation; SRMR = standardized root mean square residual.

Data Analyses and Modeling Procedures

This dissertation used panel data with four time points. The data included self-reported survey data in four time points and behavioral mobile application usage data (frequency of visitation, duration per visitation, and push notifications response latency) for 20-day study period.

To test the relationships between habit strength and mobile application use, this study implements Latent Growth Curve (LGC) models to describe group and individual differences in change within a variable and Latent Difference Scores (LDS) to examine the sequential dependency among variables based on dynamic principles (McArdle & Hamagami, 2001). Specifically, LDS analysis provides evaluations of change coupled from one variable to another over time (McArdle & Hamagami, 2001). LGC and LDS models were estimated in M*plus* V.7

(Muthén & Muthén, 2102). Full information maximum likelihood (FIML) was applied to estimate missing data because it produces unbiased parameter estimates (Collins, Schaffer, & Cam, 2001; Graham, 2003).

Additional data analyses such as repeated-measured analysis of variance (repeated-measured ANOVA), simple mean comparisons, and descriptive statistics were performed using SPSS 20.

The bivariate LDS approach prescribes change in a variable (habit strength for visiting, or frequency of visits) at any given time point as a function of prior status on the other variable (habit strength for visiting, frequency of visits, or duration of visits). For example, in the relationship between habit strength for visiting and frequency of visit, the gamma coefficients (γ_χ and γ_y) represent the cross-variable lagged influences of habit strength for visiting on change in frequency of visits and frequency of visits on change in habit strength for visiting, respectively. Figure 6 depicts this more complex bivariate LDS model, which formed the foundation for the analyses in this study. The core issue is to determine the extent to which one variable of interest influences change in the other variable of interest, and vice versa. Nine separate bivariate LDS models were developed to test the relationships among habit strength for overall application visits, frequency of visits, and duration of visits. Thus, the bivariate LDS approach tests all the directions between the variables: the directions from habit strength for application visits to frequency of visits and from frequency of visits to habit strength, and bidirectional relationship between the variables. Statistically significant paths will show the sequential dependency among variables in models.

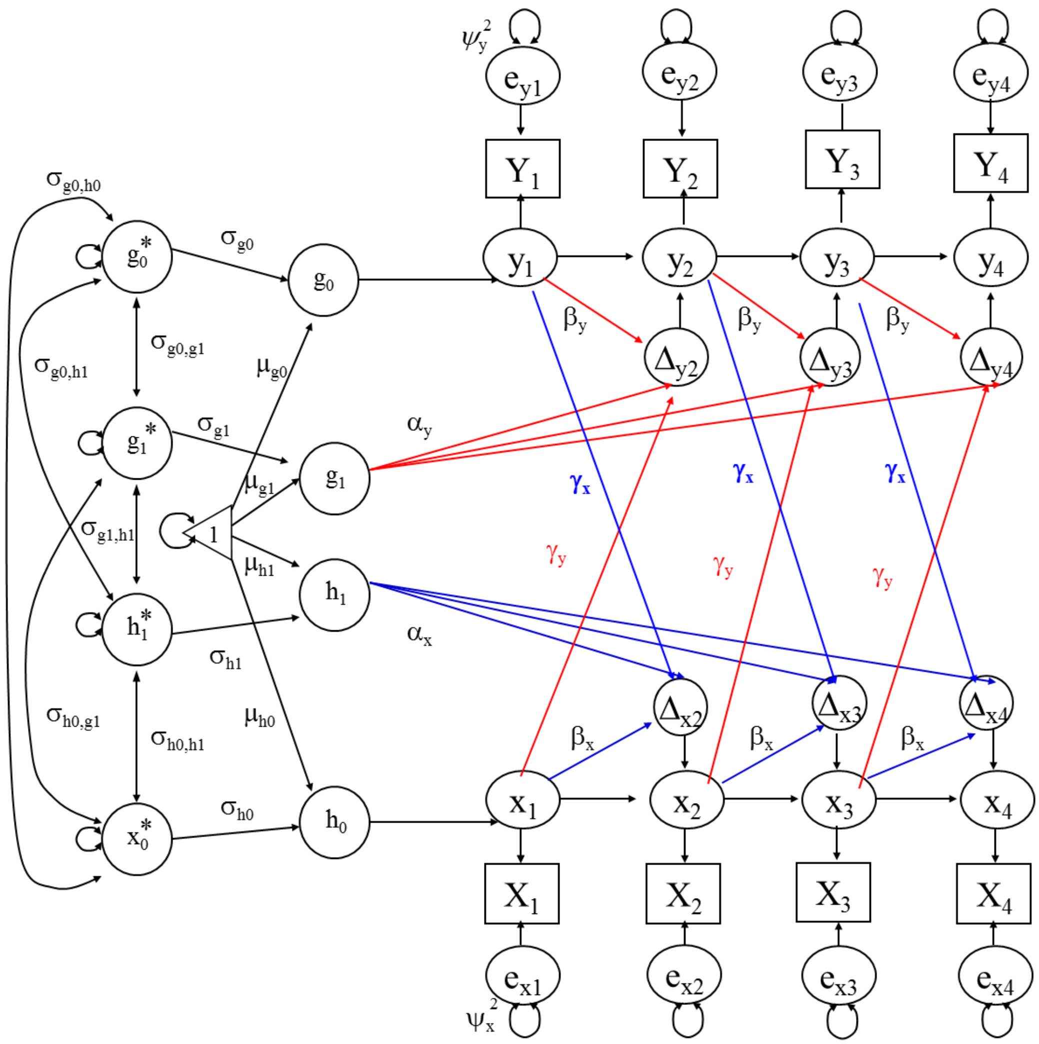


Figure 7. Bivariate dual change latent difference score model. To simplify presentation, single-indicator measurement components are depicted.

RESULTS

Data analysis was based on the 115 participants who completed surveys and used the application throughout the four waves of data collection. Table 3 illustrates the demographics of the push group and the non-push group.

Table 3

Demographics of Push Group and Non-Push Group

	Push Group (n = 63)	Non Push Group (n = 52)
Gender		
Male	19 (30.2%)	22 (42.3%)
Female	40 (63.5%)	28 (53.8%)
Missing	4 (6.3%)	2 (3.8%)
Total	63	52
Age (years)	M = 21.25, SD = 2.59	M = 21.64, SD = 2.83
Race		
Black	5 (7.9%)	4 (7.7%)
White	35 (55.6%)	25 (48.1%)
Latino	1 (1.6%)	1 (1.9%)
Asian	14 (22.2%)	15 (28.8%)
Multiracial	3 (4.8%)	4 (7.7%)
Other	1 (1.6%)	0%
Missing	4 (6.3%)	3 (5.8%)
Weather App experience		
Yes	54 (85.7%)	38 (73.1%)
No	8 (12.7%)	7 (13.5%)
Missing	1 (1.6%)	7 (13.5%)
Operating System		
iOS	45 (71.4%)	23 (44.2%)
Android	18 (28.6%)	29 (55.8%)

The mean age was 21.43 years of age (SD = 2.70) with a range from 19 to 34 years, and 59.1% of the participants were female. Over half (58.8%) of the participants had been using their current smartphone for less than 11 months (M = 10.89 months, SD = 9.89). Racially, the sample comprised of 60 Whites (52.2%), 29 Asians (25.2%), nine Blacks (7.8%), two Latinos (1.7%), eight from other racial groups (7.0%), with seven missing values. Among the 115 participants, 80% had previous experience using a weather forecast application with their smartphone and had weather application usage habit (*M* = 6.86, *SD* = 3.36). There were no significant differences between the two groups with respect to gender, $\chi 2$ (1, *N* = 110) = 1.40, $p > .05$, age $t(108) = .97$, $p > .05$, race, $\chi 2$ (5, *N* = 109) = 2.32, $p > .05$, prior experience using a mobile weather application, $\chi 2$ (1, *N* = 108) = .12, $p > .05$, and dropout rate, $\chi 2$ (1, *N* = 115) = .39, $p > .05$. There was a significant group difference between type of operating system, $\chi 2$ (1, *N* = 115) = 9.33, $p < .05$. The majority of participants in the push group were iOS users (71.4%), whereas the non-push group included more Android users (56.6%). There was also no significant difference between treatment groups for the age of the mobile phone in current use, $t(108) = .01$, $p > .05$.

There was no significant differences between groups on familiarity with a mobile weather application, $t(106) = 1.83$, $p > .05$, interest in using a weather application, $t(106) = 1.13$ $p > .05$, and prior habit strength for visiting a weather application, $t(106) = .96$, $p > .05$. Table 4 presents the age of the mobile phone in current use, level of familiarity and interest in using mobile weather application, and participant habit strength of visiting the weather application for each group.

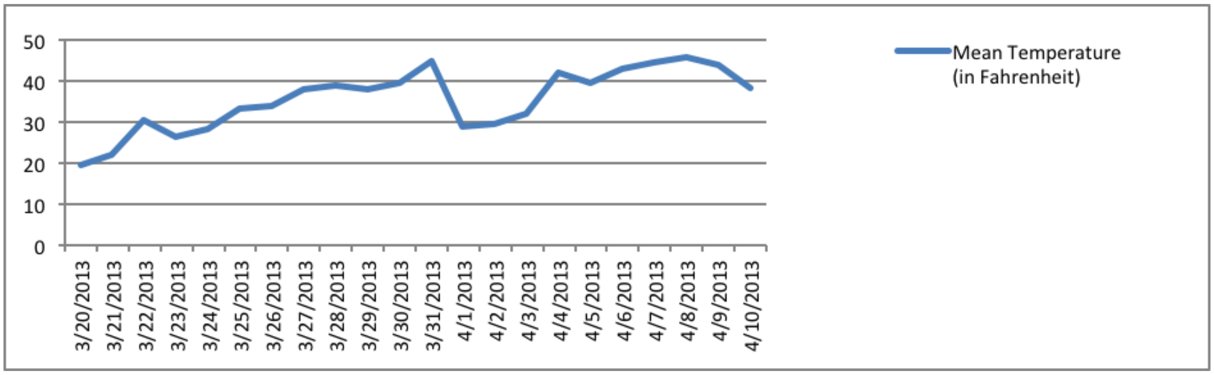
Table 4

Descriptive Statistics of Variables of Interest by Group

	Push Group (*n* = 63)		Non-Push Group (*n* = 52)	
	M	SD	M	SD
Age of the mobile phone in current use	10.85 months	11.08	10.95 months	7.13
Familiarity	5.18	1.30	5.62	1.25
Interest	5.69	1.15	5.91	1.02
Prior weather app habit strength	6.59	3.31	7.19	3.45

Weather changes

Information on temperature changes, precipitation, and weather conditions (e.g., clear, cloud, snow, or rain) was collected from the website Weather Underground (www.wundergroud.com). Figure 8 displays temperature change over time and Table 5 presents the weather data during the study.



Source. Weather Underground http://www.wunderground.com/

Figure 8. Temperature change during the 20-day study period

Table 5

Weather Information During the 20-Day Study Period

Time Point	Date	Precipitation (inch)	Weather Event
T1	3-20-2013	0.07	Snow
	3-21-2013	0.01	Snow
	3-22-2013	0.07	Snow
	3-23-2013	0	
	3-24-2013	0	
T2	3-25-2013	0.01	Snow
	3-26-2013	0.01	Snow
	3-27-2013	0	
	3-28-2013	0	
	3-29-2013	0	
T3	3-30-2013	0	
	3-31-2013	0.02	Rain
	4-1-2013	0.09	Snow
	4-2-2013	0.1	Snow
	4-3-2013	0	

Table 5 (Cont'd)

	4-4-2013	0	
	4-5-2013	0	
T4	4-6-2013	0.1	
	4-7-2013	0.1	Rain
	4-8-2013	0.35	Rain

Source. http://www.wunderground.com/

Model Viability

The first stage of analysis was to construct and evaluate a latent growth model for the habit strength measures and mobile application usage measures. An initial step in the modeling process was to test the viability of models for each manifest variable: (1) habit strength for visitation, (2) frequency of visiting, and (3) duration per visit (Barnes, Reifman, Farrell, & Dintcheff, 2000). Three separate univariate LGC models of each variable were tested in order to determine the functional forms of the growth curve with the M*plus* V.7 program using FIML estimation. Two latent factors were estimated in each LGC model, one representing the intercept (i.e., the participant's initial score of each variable) and the other representing the slope (i.e., changes in each variable over time). To represent participants' initial levels, the intercept factor was created with a fixed loading of 1.0 at each wave. To represent change in those three variables over time, the slope factor's loadings at all waves were left to be freely estimated (Duncan, Duncan, & Stoolmiller, 1994). The fit of the models was evaluated with Hu and Bentler's (1999) criteria, which suggests a cutoff value close to .95 for TLI and CFI, .06 for RMSEA, and .08 for SRMR.

A separate univariate latent growth model of each variable (i.e., habit strength for visiting, frequency of visitation, and duration per visit) were fitted in order to determine the functional form of the growth curve (Peterson et al., 2011). For all three variables, a linear growth model provided good fit. Table 6 shows results of the univariate latent growth models including model fit indices and parameter estimates.

Table 6

Univariate Latent Growth Model Results, Model Fit Indices, and Parameter Estimates by Variable

	Habit strength	Frequency of visit	Duration
Fit indices			
χ^2/df	3.80/3	2.64/3	3.39/3
CFI	1.00	1.00	1.00
TLI	1.00	1.00	.99
RMSEA	.048	.000	.034
SRMR	.038	.039	.060
Parameter estimates			
Initial status means	**5.93**	**13.44**	**24.66**
Initial status variances	**.67**	**-8.17**	**-7.43**
Change means	**3.78**	9.67	**123.60**
Change variances	**5.55**	-.93	49.67

Note. N = 115 for the models. Parameter estimates in bold are significant (p < .05). CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation.

First, for habit strength for overall application visitation, results indicate that individuals' habit strength scores for visiting significantly changed over time. The positive value of the mean slope is consistent with an increase over time and the change was significant. Second, the results of the model analysis for frequency of visits indicated that there was no difference among individuals at the beginning of the study in frequency of visitation and no significant changes over time. The mean slope's negative value is consistent with a decrease in application checking frequency, but it was not significant. Lastly, the results of the model analysis for duration indicated that there was a difference among individuals at the beginning of the study in frequency of visitation but the changes over time were not significant. The mean slope's negative value is consistent with a decrease in duration per visit to *Weather Story*.

Descriptive Statistics

Descriptive statistics for each group are provided separately in Tables 7 and 8. For the non-push group, results of the bivariate correlation tests showed a positive correlation between visiting habit strength and frequency of visitation. Prior habit strength for visiting a weather application was positively correlated with habit strength for visiting *Weather Story* at T1 only.

For the push group, however, visiting habit strength was not correlated with either frequency of visiting or duration per visit. Duration per visit at T2 was negatively correlated with habit strength for visiting *Weather Story* at T3. Prior habit strength for visiting a weather application was also positively correlated with habit strength for visiting *Weather Story* for the push group.

For both groups, prior habit strength for visiting a weather application was positively correlated with familiarity with a mobile weather application and interest in using a weather application.

Table 7

Correlations for Observed Variables for Non-Push Group

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1.PH	-																			
2.H T1	**.42**	-																		
3.H T2	.22	**.80**	-																	
4.H T3	.15	**.62**	**.89**	-																
5.H T4	.12	**.61**	**.87**	**.95**	-															
6.Visit T1	.05	.20	**.32**	**.28**	**.36**	-														
7.Visit T2	.12	.24	**.32**	.18	.20	.13	-													
8.Visit T3	.06	**.48**	**.37**	**.32**	**.38**	**.42**	**.46**	-												
9.Visit T4	.18	**.57**	**.37**	.28	**.31**	**.39**	**.33**	**.69**	-											
10.Dur T1	.10	.06	.08	.05	.06	**-.33**	.03	-.04	.03	-										
11.Dur T2	.17	.05	.21	.20	.17	.10	-.13	.07	-.04	**.46**	-									
12.Dur T3	.24	.17	.28	.28	.27	.04	.09	.02	.28	**.58**	**.36**	-								
13.Dur T4	.04	.05	-.03	-.07	-.03	.10	-.19	.04	.11	**.29**	**.49**	**.31**	-							
14.Gen	.06	.19	.19	.20	.24	.18	-.12	.17	.11	.12	.17	.15	.20	-						
15.Age	.06	.05	.00	-.00	-.01	-.15	-.12	-.17	.07	-.21	-.22	-.06	-.14	.16	-					
16.Fam	**.44**	.14	-.03	.01	-.04	-.04	-.22	-.16	-.18	.07	-.07	.02	-.04	-.00	-.16	-				
17.Inter	**.50**	**.35**	.14	.11	.05	.02	.03	.03	.08	.11	-.04	.19	-.07	.05	-.07	**.76**	-			
18.OS	.19	**.34**	.12	.10	.12	-.04	-.09	.01	.19	-.12	.01	.03	-.10	.19	.12	-.21	.01	-		
19.Race	-.07	.06	.01	.12	.08	.17	-.10	**.31**	.23	.23	**.32**	.06	.04	.10	**-.37**	.17	.18	-.12	-	
20.Phage	-.13	-.15	-.06	-.09	-.10	-.17	-.25	-.09	-.26	.19	.13	-.03	.06	-.09	.12	.11	-.15	-.26	-.12	-
M	7.19	5.99	6.29	6.58	6.61	13.15	7.19	6.35	4.73	23.34	17.02	23.15	16.31	1.56	21.64	5.62	5.91	1.56	.56	10.95
SD	3.45	2.17	2.26	2.48	2.65	7.71	5.10	4.20	3.83	8.99	7.74	23.03	9.22	.50	2.83	1.25	1.02	.50	.50	7.13
% Missing	13.5	5.8	3.8	1.9	3.8	0	0	5.8	7.7	0	0	5.8	7.7	3.8	3.8	13.5	13.5	0	13.5	3.8

Note. N = 52. Correlations in bold are significant ($p < .05$). PH = Prior habit strength for visiting a weather application; H = Visiting habit strength; Visit = Frequency of visitation; Dur = Duration per visit; Gen = Gender (1 = Male, 2 = Female); Fam = Familiarity; Inter = Interest; OS = Operating System (1= iOS, 2 = Android); Race (1 = White, 0 = Else); Phage = Age of smartphone.

Table 8

Correlations for Observed Variables for Push Group

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
1.PH	-																			
2.H T1	.26	-																		
3.H T2	.15	**.69**	-																	
4.H T3	**.32**	**.38**	**.58**	-																
5.H T4	**.27**	**.43**	**.77**	**.71**	-															
6.Visit T1	.18	.02	.09	.11	.05	-														
7.Visit T2	.09	.01	.05	-.01	.08	**.33**	-													
8.Visit T3	.16	-.02	.09	.07	.24	.25	**.71**	-												
9.Visit T4	-.03	-.06	.06	.02	.27	.30	**.37**	**.78**	-											
10.Dur T1	.04	.07	.08	-.13	.09	-.13	-.18	.15	.13	-										
11.Dur T2	.00	.08	-.09	**-.29**	-.14	-.07	.00	.04	.05	**.54**	-									
12.Dur T3	-.13	-.12	-.18	-.20	-.24	.05	.16	.21	.14	**.29**	**.51**	-								
13.Dur T4	.22	-.12	-.26	-.27	-.13	-.11	.02	.11	.19	**.38**	**.37**	**.37**	-							
14.Gen	.10	-.14	.05	.15	.18	-.02	-.14	.06	.07	.00	-.13	-.18	.03	-						
15.Age	-.05	-.02	.01	-.00	-.02	-.07	-.02	-.00	.06	-.09	-.04	-.05	.02	-.19	-					
16.Fam	**.60**	-.12	.02	.15	.16	.11	.11	.16	.02	-.08	-.19	-.03	.08	.12	-.05	-				
17.Inter	**.42**	.23	.18	.14	.25	-.07	.11	.25	.08	.18	.23	.03	.13	-.09	.07	**.31**	-			
18.OS	.01	.20	.08	-.07	-.03	**-.25**	-.18	-.15	-.12	.20	.17	.21	.12	-.25	.08	-.14	.11	-		
19.Race	-.14	-.12	-.15	-.22	-.19	.08	.05	-.06	-.01	.10	.16	.07	.01	-.07	-.16	.05	-.10	-.15	-	
20.Phage	.15	.10	.13	.07	-.03	.20	-.16	-.07	-.13	-.12	-.02	-.14	**-.30**	.02	.01	.20	.22	-.19	.15	-
M	6.59	5.99	6.29	6.03	6.58	13.60	9.33	7.77	6.25	25.81	20.31	19.98	18.33	1.68	21.25	5.18	5.69	1.29	.64	10.85
SD	3.31	2.01	2.46	2.88	2.97	6.77	6.46	5.62	5.15	14.74	12.84	17.30	12.54	.47	2.59	1.3	1.15	.46	.49	11.80
% Missing	1.6	4.8	6.3	3.2	6.3	0	12.7	15.9	17.5	0	12.7	15.9	17.5	6.3	6.3	1.6	1.6	0	12.7	6.3

Note. N = 63. Correlations in bold are significant ($p < .05$). PH = Prior habit strength for visiting a weather application; H = Visiting habit strength; Visit = Frequency of visitation; Dur = Duration per visit; Gen = Gender (1 = Male, 2 = Female); Fam = Familiarity; Inter = Interest; OS = Operating System (1= iOS, 2 = Android); Race (1 = White, 0 = Else); Phage = Age of smartphone.

To check the impact of weather on mobile application use and habit formation, bivariate correlation tests were performed among average visiting frequency, duration, average temperature changes within a day at each time point, sum of precipitation at each time point, and weather condition (i.e., rain and snow vs clear and cloudy) at each time point. Results showed that visiting frequency and duration were negatively correlated with temperature change. The temperature data shows that temperature changes were larger on warmer days than cold days during the study period. This suggests that participants did not worry about the weather when it was relatively nice so they did not visit the application to check the weather. Table 9 illustrates correlations for weather information and mobile application usage behaviors.

Table 9

Correlations for Weather Information and Mobile Application Usage Behaviors

	1	2	3	4	5
1. Visiting	-				
2. Duration	**.98**	-			
3. Temperature changes	**-.99**	**-.98**	-		
4. Precipitation	-.46	-.41	.55	-	
5. Weather conditions	.54	.65	-.55	-.38	-

Note. The units of analysis were the survey periods (T1, T2, T3, and T4). Correlations in bold are significant ($p < .05$); Weather conditions (Snow/rain = 1, clear/cloud = 0)

Habit Development

To test whether participants established a habit for visiting *Weather Story* that was as strong as prior habit strength for visiting a weather application during the 20-day study period, a paired-samples t-test comparing prior habit strength and habit for visiting *Weather Story* was performed. Results showed that habit strength for visiting *Weather Story* did not reach prior habit strength, but they were not significantly different.

For the non-push group, a paired-samples t-test showed that prior habit strength was significantly higher than habit strength for visiting Weather Story at T1, $p < .05$, but not higher at T2, T3, and T4, $p > .05$. For the push group, prior habit strength was not significantly higher than habit strength for visiting *Weather Story* at any of the four time points, $p > .05$.

Effect of Push Notification Alerts on Habit Strength and Application Use

The first hypothesis proposed that push notification alerts would act as salient external cues influencing habit formation for mobile application visitation and frequency of visits. In particular, H1a predicted that users who receive push notifications from the application would have higher levels of habit strength for application use than the non-push group through faster growth in habit strength for visiting the application than those who did not receive push notification alerts. This hypothesis was tested by comparing the scores of habit strength for overall application visitation between the push and non-push groups. A repeated-measures ANOVA was conducted with habit strength for mobile application use over time as the within-subjects factor and push notification condition (push group versus non-push group) as the between-subjects factor.

Table 10

Repeated-Measures ANOVA Results for Habit Strength over Time between Push Group and Non-Push Group

	DF	*F*	*P*
Habit Strength	3	4.20	<.05
Group	1	.03	>.05
Habit Strength X Group	3	.47	>.05

Note. Using Mauchly’s test, it was found that the assumption of sphericity was violated, Mauchly’s W = .55, $\chi2$ (5) = 57.45, $p < .05$, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon < .75$) (Girden, 1992).

Although the within-subjects effect indicated significant changes in habit strength for mobile application use over time, the interaction effect demonstrated that the trajectory of the push and non-push groups did not differ over time. The between-subjects effect indicated that there was no significant difference between groups. This suggests that differences among individual participants were significant whereas the group differences were not. An additional mean comparison test between the push group and non-push group at Time 3 also revealed no group difference, $F(1, 110) = 1.15$, $p > .05$. Figure 9 illustrates the pattern of change in habit strength in *Weather Story* visitation over time in the push group and non-push group.

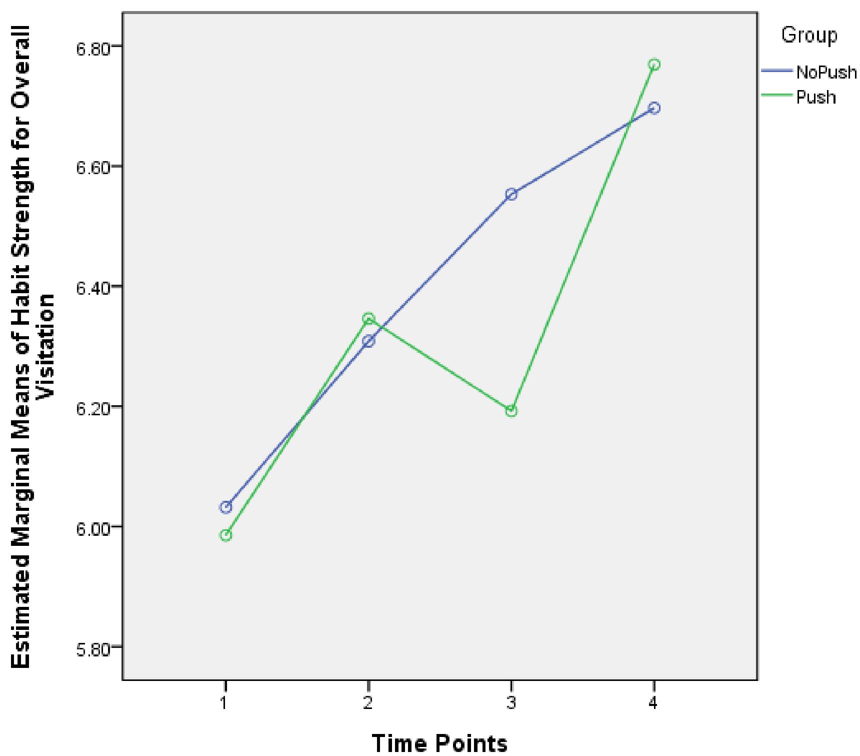


Figure 9. Plot of habit strength for overall *Weather Story* visitation for the push and non-push groups across the four time points.

Although this dissertation expected these differences would come from group differences (i.e., receiving push notification alerts vs. not receiving them), the results of the repeated

ANOVA test showed the variance in habit strength for overall visitation over time was not related to push notifications. Based on the results, this dissertation explored what factors were related to individual differences in habit strength for overall visitation. Gender, age, race, age of smartphone in current use, initial interest and familiarity using weather application, and prior habit strength were tested. Results of a bivariate correlation test showed that prior habit strength for a weather application visitation was a significant factor that influenced habit strength for visiting *Weather Story* at Time1, Time 3, and Time 4.

Table 11

Correlations for Habit Strength, Demographic, and Background Variables

	1	2	3	4	5	6	7	8	9	10	11
1. HT1	-										
2. HT2	**.74**	-									
3. HT3	**.48**	**.71**	-								
4. HT4	**.51**	**.81**	**.81**	-							
5. Gender	.03	.11	.17	**.21**	-						
6. Age	.02	.00	.02	.01	-.01	-					
7. Race	-.03	-.08	-.10	-.09	.01	**-.29**	-				
8. Phage	.01	.07	.02	-.05	-.02	.04	.04	-			
9. Familiarity	-.01	.01	.11	.09	.04	-.07	.08	.17	-		
10. Interest	**.28**	.16	.14	.18	-.04	.04	.00	.11	**.49**	-	
11. PH	**.33**	.18	**.26**	**.21**	.07	.01	-.11	.06	**.54**	**.45**	-
M	6.00	6.29	6.29	6.62	1.63	21.49	.59	10.86	5.37	5.80	6.86
SD	2.07	2.35	2.70	2.81	.49	2.76	.49	9.86	1.29	1.10	3.36
% Missing	5.2	5.2	2.6	5.2	5.2	5.2	12.9	5.2	6.9	6.9	6.9

Note. N = 115. Correlations in bold are significant ($p < .05$). Phage = Age of mobile phone in current use; PH = Prior habit strength; HT1, 2, 3, and 4 = Habit Strength for overall *Weather Story* visitation at Time1, Time2, Time3, and Time 4; Gender (1 = Male, 2 = Female); Race (1 = White, 0 = Else)

Response latency was calculated by comparing the time at which the push notification was delivered with the time of the visit to the application. A total of 77 push notification messages were sent to the group receiving push notifications, and the average number of push notification sent per day was 2.57 (*SD* = .63) with a range of two to four push notifications. Descriptive statistics show the use of push notifications (clicking push notification delivered) was highly negatively skewed. Among the 63 users receiving push notification messages, 32 participants actually clicked the notifications at least once (range from 1 to 16). The average number of clicked push notifications was 1.08 (*SD* = 1.60) at Time 1, .68 (*SD* = 1.35) at Time 2, .48 (*SD* = 1.09) at Time 3, and .40 (*SD* = .91) at Time 4. The average response latency to push notification (the time notification delivered – the time notification clicked) was 3.98 minutes (*SD* = 8.45) at Time 1, 5.32 minutes (*SD* = 20.52) at Time 2, 1.66 minutes (*SD* = 4.92) at Time 3, and 1.19 minutes (*SD* = 4.58) at Time 4.

To fully understand the effect of push notification on habit formation, this study conducted post hoc analysis with three groups: (1) a non-push group who did not received any push notification, (2) a non-responding group who received push notifications but never clicked, and (3) a responding group who received push notifications and clicked at least once. Repeated-measured ANOVA tests were conducted with habit strength for mobile application use over time as the within-subjects factor and the condition of use of push notification (i.e., non-push group who did not received any push notification vs non-responding group who received push notifications but never clicked vs responding group who received push notifications and clicked at least once) as the between-subjects factor. The results are presented in Table 12.

Table 12

Repeated-Measures ANOVA Results for Frequency of Visits over Time between Non-Push Group, Non Responding Group, and Responding Group

	DF	*F*	*P*
Habit Strength	3	4.02	<.05
Group	2	.01	>.05
Habit Strength X Group	6	1.53	>.05

Note. Using Mauchly's test, it was found that the assumption of sphericity was violated, Mauchly's W = .53, $\chi 2$ (5) = 58.73, $p < .05$, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon < .75$) (Girden, 1992).

The within-subjects effect indicated significant changes in habit strength for mobile application use over time in all three groups. However, the interaction effect demonstrated that the trajectory of those three groups did not differ over time and there was no significant difference in habit strength scores among the groups at any of the time points. This indicates that participants' habit strength significantly changed over time whereas there were no group differences to changes in habit strength.

H1b predicted that users who receive push notifications from the application would visit the application more frequently than those who did not receive push notification alerts. Repeated-measures ANOVA tests were performed to determine if there were group differences in frequency of visits to *Weather Story*. Table 13 presents the results between the push group and non-push group.

Table 13

Repeated-Measures ANOVA Results for Frequency of Visits over Time between Push Group and Non-Push Group

	DF	*F*	*P*
Frequency	3	81.76	<.05
Group	1	4.33	<.05
Frequency X Group	3	.24	>.05

Note. Using Mauchly's test, it was found that the assumption of sphericity was violated, Mauchly's W = .54, $\chi2$ (5) = 59.16, $p < .05$, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon < .75$) (Girden, 1992).

The within-subjects effect indicated significant changes in frequency of visitation over time. The between-subjects effect found that there was a significant difference between groups. However, the interaction effect demonstrated that the trajectory of visitation between the push group and non-push group did not differ over time. Figure 10 illustrates the pattern of change in frequency of visitation over time in the push group and non-push group.

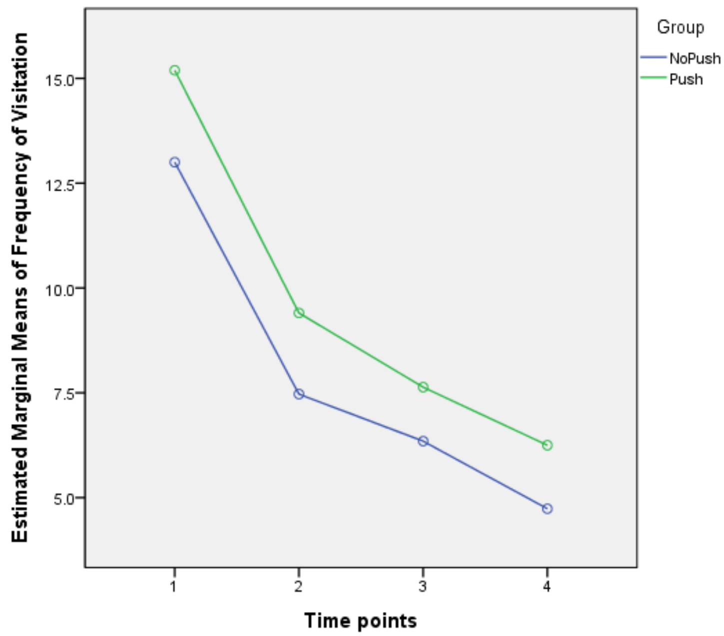


Figure 10. Plot of frequency of *Weather Story* visitation for the push and non-push groups across the four time points.

In addition, a repeated-measures ANOVA was performed to test differences in duration per visit to *Weather Story*. Table 14 presents the results between the two groups.

Table 14

Repeated-Measures ANOVA Results for Duration per Visit over Time between Push Group and Non-Push Group

	DF	*F*	*P*
Duration	3	81.73	<.05
Group	1	.21	>.05
Duration X Group	3	1.36	>.05

Note. Using Mauchly's test, it was found that the assumption of sphericity was violated, Mauchly's W = .47, $\chi 2$ (5) = 73.33, $p < .05$, therefore degrees of freedom were corrected using Greenhouse-Geisser estimates of sphericity ($\varepsilon < .75$) (Girden, 1992).

The within-subjects effect indicated significant changes in duration per visit to *Weather Story* over time. However, the between-subjects effect and interaction effect demonstrated that there was no significant group difference and that the trajectory of visitation between the push group and non-push group did not differ over time. Figure 11 illustrates the pattern of change in frequency of visitation over time in the push group and non-push group.

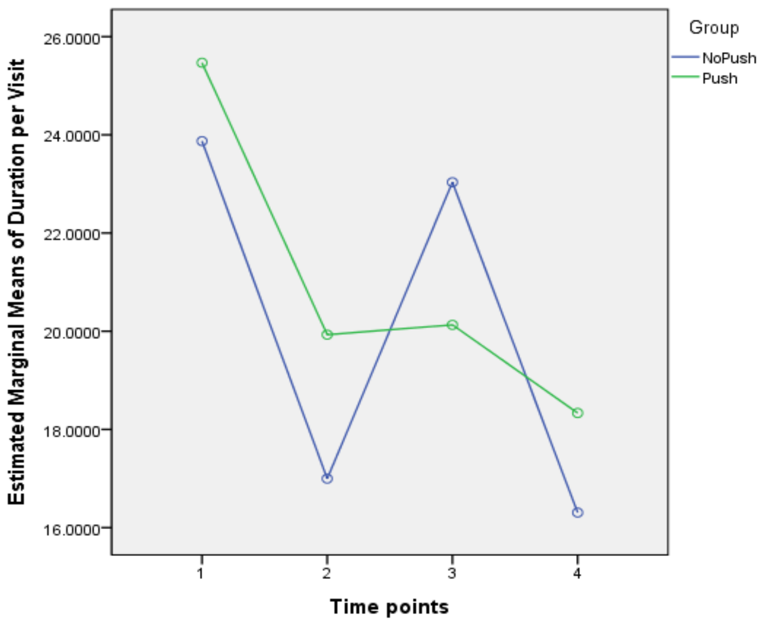


Figure 11. Plot of duration per visit to *Weather Story* for the push and non-push group across the four time points.

Causal Relationship between Habit for Mobile Application Visitation and the Behaviors of Frequency of Visitation and Duration on Application

The second set of hypotheses proposed a causal relationship between habit strength for overall visitation and frequency of visitation (H2a) and a causal relationship between habit strength and duration per visit on application (H2b). In addition, the research question proposed an association between frequency of visitation and duration per visit to the application (RQ). This study took the perspective that suggests that habits influence media use based on evidence of the effects of habit in technology use (LaRose & Eastin, 2004; LaRose et al., 2003; Soror et al., 2010)

This dissertation had two different strategies to test relationships among habit strength for application visitation, frequency of visitation, and duration per visit to the application. First, bivariate LDS models combining two groups together were estimated. According to the repeated ANOVA that tested the group difference in habit strength for application visitation, individual differences were significant whereas group differences were not. Focusing on individual differences, the models including both groups together would explain the association between habit strength and application usage behaviors. Second, bivariate LDS models for each group were estimated separately to see the effect of push notifications on the association between habit strength and application usage behaviors. In addition, since habit strength for overall visitation correlated with prior habit strength for visiting a weather application, this dissertation also tested the effect of prior habit strength in the model. For this, prior habit strength was added to each LDS model as a covariate.

H2a predicted that habit strength for mobile application visitation would positively predict the frequency of mobile application visits. Three separated bivariate dual change models were tested for H2a: one including both groups together, another including only the non-push group, and one including only the push group.

First, Table 15 presents results of the model including *both groups* and the association between habit strength for overall visitation and frequency of visits.

Table 15

Bivariate Latent Difference Score Model for Habit Strength for Overall Visitation and Frequency of Visiting Weather Story for Both Groups

Fit indices	No Covariate		Prior Habit as Covariate	
χ^2/df	54.39/17		63.82/21	
CFI	.92		.91	
TLI	.87		.84	
RMSEA	.138 (90% CI = .09 - .180)		.138 (90% CI = .100-.177)	
SRMR	.076		.062	
Parameter estimates	*H*	*Visit*	*H*	*Visit*
Initial status means	5.95 (**31.57**)	13.39 (**20.01**)	5.95 (**31.57**)	13.39 (**20.01**)
Initial status variances	2.66 (**6.31**)	42.42 (**6.17**)	2.66 (**6.31**)	42.42 (**6.17**)
Change means	3.67 (**7.72**)	6.85 (**3.82**)	3.67 (**7.72**)	6.85 (**3.82**)
Change variances	2.66 (**6.31**)	26.17 (**4.97**)	2.66 (**6.31**)	26.17 (**4.97**)
Initial status with constant change	1.59 (**3.94**)	14.47 (**3.06**)	1.48(**3.79**)	14.37(**2.85**)
H – Visit association				
$H_1 \rightarrow \Delta Visit_2$	.37 (1.17)		.23(.68)	
$H_2 \rightarrow \Delta Visit_3$	.30 (1.14)		.25(.91)	
$H_3 \rightarrow \Delta Visit_4$	.19 (.75)		.15(.56)	
$Visit_1 \rightarrow \Delta H_2$	.01 (.59)		.02(.65)	
$Visit_2 \rightarrow \Delta H_3$	.02 (.38)		.03(.58)	
$Visit_3 \rightarrow \Delta H_4$	.04 (.98)		.04(.91)	
Covariate				
Prior habit → Initial status of H			.25(**3.28**)	
Prior habit → Change of H			.13(**2.01**)	
Prior habit → Initial status of Visit			.28(.97)	
Prior habit → Change of Visit			.22(.90)	

Note. *N* = 115 for the model without covariate and *N* = 107 for the model with covariate. Entries in the table's lower portion are parameter estimates with associated critical ratios (CRs) in parentheses. Salient CRs greater than 1.96 appear in bold. H = habit strength for overall visitation; Visit = frequency of visiting *Weather Story*; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; CI = confidence interval; $H_{t-1} \rightarrow \Delta Visit_t$ = latent score of H predicting subsequent latent difference score of Visit; $Visit_{t-1} \rightarrow \Delta H_t$ = latent scores of Visit predicting subsequent latent difference score of H.

For the model without a covariate, results showed that the chi-square value was 54.39, with 17 degrees of freedom and an associated probability of .00. CFI was acceptable (.92) but TLI was not large enough (.87). RMSEA and SRMR were high (.138 and .076, respectively). For the model with prior habit strength as a covariate, the chi-square value was 63.82, with 21 degrees of freedom and an associated probability of .00. CFI was acceptable (.91) but TLI was not large enough (.84). RMSEA was high (.138) and SRMR was acceptable (.062). Overall, the model did not fit the data. The parameter estimates showed there was no significant association between habit strength for overall visitation and frequency of visitation. The effects of prior habit strength on the initial status and change of habit strength for visitation were significant.

Second, Table 16 presents results of the model including *only the non-push group* and the association between habit strength for overall visitation and frequency of visits.

Table 16

Bivariate Latent Difference Score Model for Habit Strength for Overall Visitation and Frequency of Visiting Weather Story for Non-Push Group

Fit indices	No Covariate		Prior Habit as Covariate	
χ^2/df	69.46/17		56.34/21	
CFI	.83		.88	
TLI	.72		.79	
RMSEA	.244 (90% CI = .186 - .305)		.192 (90% CI = .133-.255)	
SRMR	.219		.163	
Parameter estimates	*H*	*Visit*	*H*	*Visit*
Initial status means	5.92 (**23.10**)	13.11 (**12.33**)	5.92 (**23.10**)	13.11 (**12.33**)
Initial status variances	2.94 (**5.81**)	45.75 (**3.92**)	2.94 (**5.81**)	45.75 (**3.92**)
Change means	2.58 (**1.63**)	-.46 (-.27)	2.58 (**1.63**)	-.46 (-.27)
Change variances	2.94 (**5.81**)	.46 (1.11)	2.94 (**5.81**)	.46 (1.11)
Initial status with constant change	.98 (1.04)	-.67 (-.14)	1.91(**2.77**)	-7.86(-.81)
H – Visit association				
$H_1 \rightarrow \Delta Visit_2$	.82 (**4.64**)		.71(**2.39**)	
$H_2 \rightarrow \Delta Visit_3$	-.40 (-.85)		-.34(-.67)	
$H_3 \rightarrow \Delta Visit_4$	.02 (.09)		-.32(-.62)	
$Visit_1 \rightarrow \Delta H_2$	.04 (.84)		.01(.18)	
$Visit_2 \rightarrow \Delta H_3$	.14 (.57)		-.07(-.46)	
$Visit_3 \rightarrow \Delta H_4$	.20 (1.06)		.04(.33)	
Covariate				
Prior habit → Initial status of H			.34(**3.05**)	
Prior habit → Change of H			.06(.57)	
Prior habit → Initial status of Visit			.09(.19)	
Prior habit → Change of Visit			-.07(-.73)	

Note. N = 52 for the model without covariate and N = 45 for the model with covariate. Entries in the table's lower portion are parameter estimates with associated critical ratios (CRs) in parentheses. Salient CRs greater than 1.96 appear in bold. H = habit strength for overall visitation; Visit = frequency of visiting *Weather Story*; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; CI = confidence interval; $H_{t-1} \rightarrow \Delta Visit_t$ = latent score of H predicting subsequent latent difference score of Visit; $Visit_{t-1} \rightarrow \Delta H_t$ = latent scores of Visit predicting subsequent latent difference score of H.

Results of the bivariate LDS model without a covariate including only the non-push group showed that the chi-square value was 69.46, with 17 degrees of freedom and an associated probability of .00. CFI and TLI were not good (.83 and .72, respectively). RMSEA and SRMR were high (.244 and .219, respectively). Meanwhile, for the model with prior habit strength as a covariate, the chi-square value was 56.34, with 21 degrees of freedom and an associated probability of .00. CFI and TLI were not good (.88 and .79, respectively). RMSEA and SRMR were high (.192 and .163, respectively). Habit strength at T1 positively predicted the subsequent change of frequency of visits for both the models with and without a covariate. The effect of prior habit strength influenced the initial status of habit strength for overall visitation. Overall, the model did not fit the data.

Lastly, Table 17 presents results of the model including *only the push group* and the association between habit strength for overall visitation and frequency of visits.

Table 17

Bivariate Latent Difference Score Model for Habit Strength for Overall Visitation and Frequency of Visiting Weather Story for Push Group

Fit indices	No Covariate		Prior Habit as Covariate	
χ^2/df	53.05/17		64.55/21	
CFI	.84		.82	
TLI	.73		.68	
RMSEA	.183 (90% CI = .129 - .240)		.183 (90% CI = .133-.235)	
SRMR	.171		.142	
Parameter estimates	*H*	*Visit*	*H*	*Visit*
Initial status means	5.93 (**22.04**)	13.67 (**17.57**)	5.93 (**22.04**)	13.67 (**17.57**)
Initial status variances	2.38 (**3.86**)	23.81 (**3.54**)	2.38 (**3.86**)	23.81 (**3.54**)
Change means	3.17 (**4.16**)	-4.46 (-1.67)	3.17 (**4.16**)	-4.46 (-1.67)
Change variances	2.38 (**3.86**)	1.97 (.58)	2.38 (**3.86**)	1.97 (.58)
Initial status with constant change	1.18 (**2.32**)	-7.32 (-1.18)	.94(**2.03**)	-5.51(-.95)
H – Visit association				
$H_1 \rightarrow \Delta Visit_2$	-1.54 (**-3.65**)		-1.53(**-3.50**)	
$H_2 \rightarrow \Delta Visit_3$	.45 (1.67)		.40(1.47)	
$H_3 \rightarrow \Delta Visit_4$	.12 (.43)		.13(.45)	
$Visit_1 \rightarrow \Delta H_2$	.02 (.36)		-.01(-.14)	
$Visit_2 \rightarrow \Delta H_3$	.04 (.72)		.03(.62)	
$Visit_3 \rightarrow \Delta H_4$	.03 (.45)		-.00(-.05)	
Covariate				
Prior habit → Initial status of H			.15(1.49)	
Prior habit → Change of H			.20(**2.19**)	
Prior habit → Initial status of Visit			.55(1.90)	
Prior habit → Change of Visit			-.17(-.96)	

Table 17 (Cont'd)

Note. N = 63 for the model without covariate and N = 62 for the model with covariate. Entries in the table's lower portion are parameter estimates with associated critical ratios (CRs) in parentheses. Salient CRs greater than 1.96 appear in bold. H = habit strength for overall visitation; Visit = frequency of visiting *Weather Story*; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; CI = confidence interval; $H_{t-1} \rightarrow \Delta Visit_t$ = latent score of H predicting subsequent latent difference score of Visit; $Visit_{t-1} \rightarrow \Delta H_t$ = latent scores of Visit predicting subsequent latent difference score of H.

Like the other two models, results of the bivariate LDS model including only the push group showed a bad model fit to the data. Overall, based on the results of the three separatebivariate dual change models examining the association between habit strength for overall visitation and frequency of visits, H2a was not supported; this study did not clearly determine the causal relationship between habit strength and frequency of visits. However, both groups showed similar patterns of association.

H2b proposed that habit strength for mobile application visitation would positively predict the duration of application visits on the mobile application. To test this hypothesis, three separated bivariate dual change models were tested: one including both groups together, another including only the non-push group, and one including only the push group. Table 18 presents results of the model including *both groups* and the association between habit strength for overall visitation and duration per visit to *Weather Story*.

Table 18

Bivariate Latent Difference Score Model for Habit Strength for Overall Visitation and Duration per Visit to Weather Story for Both Groups

Fit indices	No Covariate	Prior Habit as Covariate
χ^2/df	71.56/17	78.77/21
CFI	.86	.85
TLI	.77	.75
RMSEA	.167 (90% CI = .128 - .208)	.160 (90% CI = .124 -.199)
SRMR	.143	.130

Table 18 (Cont'd)

Parameter estimates	*H*	*Duration*	*H*	*Duration*
Initial status means	5.94 (**32.41**)	24.38 (**20.69**)	5.94 (**32.41**)	24.38 (**20.69**)
Initial status variances	2.47 (**6.15**)	34.02 (1.51)	2.47 (**6.15**)	34.02 (1.51)
Change means	3.45 (**6.14**)	31.39 (**5.42**)	3.45 (**6.14**)	31.39 (**5.42**)
Change variances	2.47 (**6.15**)	251.29 (**4.24**)	2.47 (**6.15**)	251.29 (**4.24**)
Initial status with constant change	1.45 (**3.72**)	135.56 (4.22)	.94(**2.03**)	-5.51(-.95)
H – Duration association				
$H_1 \rightarrow \Delta Duration_2$	1.30 (1.70)		.94(1.13)	
$H_2 \rightarrow \Delta Duration_3$	-1.85 (**-2.15**)		-2.56(**-2.52**)	
$H_3 \rightarrow \Delta Duration_4$	-.49 (-.67)		-.88(-1.04)	
$Duration_1 \rightarrow \Delta H_2$	.02 (.98)		.05(**2.15**)	
$Duration_2 \rightarrow \Delta H_3$	-.03 (-1.36)		-.02(-1.09)	
$Duration_3 \rightarrow \Delta H_4$	.02 (1.76)		.03(**2.45**)	
Covariate				
Prior habit → Initial status of H			.27(**3.50**)	
Prior habit → Change of H			.13(**1.99**)	
Prior habit → Initial status of Duration			.16(.036)	
Prior habit → Change of Duration			.60(.77)	

Note. *N* = 115 for the model without covariate and *N* = 107 for the model with covariate. Entries in the table's lower portion are parameter estimates with associated critical ratios (CRs) in parentheses. Salient CRs greater than 1.96 appear in bold. H = habit strength for overall visitation; Duration = duration per visit to Weather Story; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; CI = confidence interval; $H_{t-1} \rightarrow \Delta Duration_t$ = latent score of H predicting subsequent latent difference score of Duration; $Duration_{t-1} \rightarrow \Delta H_t$ = latent scores of Duration predicting subsequent latent difference score of H.

The effects of prior habit strength for visiting a weather application were tested as a covariate for the models including habit strength for overall visitation. For the model without a covariate, results showed that the chi-square value was 71.56, with 17 degrees of freedom and an associated probability of .00. CFI and TLI were not good (.86 and .77, respectively). RMSEA and SRMR were high (.167 and .143, respectively). For the model with a covariate, the chi-square value was 78.77, with 21 degrees of freedom and an associated probability of .00. CFI and TLI were not good (.85 and .75, respectively). RMSEA and SRMR were high (.160 and .130, respectively). For the model without a covariate, habit strength for overall visitation at T2 predicted subsequent changes in duration per visit. However, for the model with prior habit strength as a covariate, duration at T1 and at T3 positively predicted subsequent changes in habit strength for visitation. The effects of prior habit strength on initial status and changes of habit strength for overall visitation were significant. Overall, the model did not fit the data.

Table 19 presents results of the model including *only the non-push group* and the association between habit strength for overall visitation and duration per visit.

Table 19

Bivariate Latent Difference Score Model for Habit Strength for Overall Visitation and Duration per Visit to Weather Story for Non-Push Group

Fit indices	No Covariate		Prior Habit as Covariate	
χ^2/df	72.02/17		61.87/21	
CFI	.81		.86	
TLI	.68		.75	
RMSEA	.249 (90% CI = .192 - .310)		.208 (90% CI = .149 -.269)	
SRMR	.338		.308	
Parameter estimates	*H*	*Duration*	*H*	*Duration*
Initial status means	5.91 (**22.16**)	22.37 (**14.49**)	5.91 (**22.16**)	22.37 (**14.49**)
Initial status variances	3.19 (**5.19**)	8.00 (.37)	3.19 (**5.19**)	8.00 (.37)
Change means	4.05 (**7.60**)	28.53 (**4.14**)	4.05 (**7.60**)	28.53 (**4.14**)
Change variances	3.19 (**5.19**)	206.46 (**2.95**)	3.19 (**5.19**)	206.46 (**2.95**)
Initial status with constant change	1.91 (**3.25**)	88.01 (**2.51**)	.94(**2.03**)	-5.51(-.95)
H – Duration association				
$H_1 \rightarrow \Delta Duration_2$	2.55 (**4.23**)		2.70(**4.40**)	
$H_2 \rightarrow \Delta Duration_3$	-2.11 (-1.90)		-1.76(-1.70)	
$H_3 \rightarrow \Delta Duration_4$	-.07 (-.08)		.24(.25)	
$Duration_1 \rightarrow \Delta H_2$	-.00 (-.16)		.01(.64)	
$Duration_2 \rightarrow \Delta H_3$	-.03 (-1.49)		-.00(-.18)	
$Duration_3 \rightarrow \Delta H_4$	-.00 (-.22)		.00(.16)	
Covariate				
Prior habit → Initial status of H			.37(**3.32)**	
Prior habit → Change of H			.06(.56)	
Prior habit → Initial status of Duration			.52(.95)	
Prior habit → Change of Duration			.98(.95)	

Note. *N* = 52 for the model without covariate and *N* = 45 for the model with covariate. Entries in the table's lower portion are parameter estimates with associated critical ratios (CRs) in parentheses. Salient CRs greater than 1.96 appear in bold. H = habit strength for overall visitation; Duration = duration per visit to *Weather Story*; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; CI = confidence interval; $H_{t-1} \rightarrow \Delta Duration_t$ = latent score of H predicting subsequent latent difference score of Duration; $Duration_{t-1} \rightarrow \Delta H_t$ = latent scores of Duration predicting subsequent latent difference score of H.

Results of the bivariate LDS model without a covariate including only the non-push group showed that the chi-square value was 72.02, with 17 degrees of freedom and an associated probability of .00. CFI and TLI were not good (.81 and .68, respectively). RMSEA and SRMR were high (.249 and .338, respectively). For the model with a covariate, the chi-square value was 61.87, with 21 degrees of freedom and an associated probability of .00. CFI and TLI were not good (.86 and .75, respectively). RMSEA and SRMR were high (.208 and .308, respectively).

For the model without a covariate and with prior habit strength as a covariate, habit strength at T1 predicted subsequent change on duration. The effect of prior habit strength on initial status of habit strength for overall visitation was significant. Overall, the model did not fit the data.

Table 20 presents results of the model including *only the push group* and the association between habit strength for overall visitation and duration per visit.

Table 20

Bivariate Latent Difference Score Model for Habit Strength for Overall Visitation and Duration per Visit to Weather Story for Push Group

Fit indices		
χ^2/df	33.12/17	
CFI	.91	
TLI	.84	
RMSEA	.123 (90% CI = .058 - .185)	
SRMR	.07	
Parameter estimates	*H*	*Duration*
Initial status means	5.92 (**22.22**)	25.51 (**13.15**)
Initial status variances	2.00 (**3.53**)	127.09 (**3.20**)
Change means	3.23 (**3.42**)	-25.11 (-.58)
Change variances	2.00 (**3.53**)	151.71 (.33)
Initial status with constant change	1.25 (**2.43**)	-139.01 (-.64)
H – Duration association		
$H_1 \rightarrow \Delta Duration_2$	-.78 (-.60)	
$H_2 \rightarrow \Delta Duration_3$	-1.29 (-1.15)	
$H_3 \rightarrow \Delta Duration_4$	1.96 (.84)	
$Duration_1 \rightarrow \Delta H_2$	.00 (.12)	
$Duration_2 \rightarrow \Delta H_3$	-.05 (-1.39)	
$Duration_3 \rightarrow \Delta H_4$	.02 (.96)	

Note. *N* = 63. Entries in the table's lower portion are parameter estimates with associated critical ratios (CRs) in parentheses. Salient CRs greater than 1.96 appear in bold. H = habit strength for overall visitation; Duration = duration per visit to *Weather Story*; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; CI = confidence interval; $H_{t-1} \rightarrow \Delta Duration_t$ = latent score of H predicting subsequent latent difference score of Duration; $Duration_{t-1} \rightarrow \Delta H_t$ = latent scores of Duration predicting subsequent latent difference score of H.

Results of the bivariate LDS model including only the push group showed that the chi-square value was 33.12, with 17 degrees of freedom and an associated probability of .01. CFI and TLI were not good (.91 and .84, respectively). RMSEA and SRMR were high (.123 and .07, respectively). Overall, the model did not fit the data. The model with prior habit strength as a covariate did not converge. Overall, based on the results of the three separate bivariate dual change models examining the association between habit strength for overall visitation and frequency of visits, H2b was not supported.

The research question asked whether frequency of visits would positively predict the duration of application visits on the mobile application. Three bivariate LDS models were tested for H2c to estimate the association between frequency of visitation and duration per visit to *Weather Story* for both groups together, for the non-push group, and for the push group separately.

First, Table 21 presents results of the model including *both groups*.

Table 21

Bivariate Latent Difference Score Model for Frequency of Visiting and Duration per Visit to Weather Story for Both Groups

Fit indices		
χ^2/df	82.60/17	
CFI	.72	
TLI	.54	
RMSEA	.183 (90% CI = .145 - .224)	
SRMR	.155	
Parameter estimates	*Visit*	*Duration*
Initial status means	13.38 (**20.02**)	24.80 (**20.51**)
Initial status variances	43.20 (6.**14**)	62.56 (**3.75**)
Change means	2.00 (**.67**)	15.87 (**3.97**)
Change variances	21.75 (**4.03**)	62.56 (**3.75**)
Initial status with constant change	11.75 (**2.55**)	54.69 (**3.44**)

Table 21 (Cont'd)

Visit - Duration association	
$Visit_1 \rightarrow \Delta Duration_2$	.12 (.73)
$Visit_2 \rightarrow \Delta Duration_3$	-1.23 (-1.86)
$Visit_3 \rightarrow \Delta Duration_4$	-.10 (-.18)
$Duration_1 \rightarrow \Delta Visit_2$	.30 (**1.99**)
$Duration_2 \rightarrow \Delta Visit_3$	.35 (1.84)
$Duration_3 \rightarrow \Delta Visit_4$	.18 (**2.39**)

Note. N = 115. Entries in the table's lower portion are parameter estimates with associated critical ratios (CRs) in parentheses. Salient CRs greater than 1.96 appear in bold. Visit = frequency of visiting *Weather Story*; Duration = duration per visit to *Weather Story*; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; CI = confidence interval; $Visit_{t-1} \rightarrow \Delta Duration_t$ = latent score of Visit predicting subsequent latent difference score of Duration; $Duration_{t-1} \rightarrow \Delta Visit_t$ = latent scores of Duration predicting subsequent latent difference score of Visit.

For this model, results showed that the chi-square value was 82.60, with 17 degrees of freedom and an associated probability of .00. CFI and TLI were small (.72 and .54, respectively). RMSEA and SRMR were high (.183 and .155, respectively). Overall, the model did not fit the data.

Second, Table 22 presents results of the model including *only the non-push group* and the association between habit strength for overall visitation and frequency of visits.

Table 22

Bivariate Latent Difference Score Model for Frequency of Visiting and Duration per Visit to Weather Story for Non-Push Group

Fit indices		
χ^2/df	67.47/17	
CFI	.53	
TLI	.22	
RMSEA	.239 (90% CI = .181 - .300)	
SRMR	.167	
Parameter estimates	*Visit*	*Duration*
Initial status means	13.14 (**12.74**)	23.37 (**19.71**)
Initial status variances	40.01 (**3.74**)	22.66 (**2.02**)
Change means	5.32 (**2.13**)	13.76 (**3.49**)
Change variances	5.57 (1.60)	22.66 (**2.02**)
Initial status with constant change	12.91 (**2.30**)	25.07 (**2.42**)

Table 22 (Cont'd)

Visit - Duration association	
$Visit_1 \rightarrow \Delta Duration_2$	.34 (**2.22**)
$Visit_2 \rightarrow \Delta Duration_3$	-11.66 (-1.70)
$Visit_3 \rightarrow \Delta Duration_4$	.47 (.98)
$Duration_1 \rightarrow \Delta Visit_2$	.20 (**2.35**)
$Duration_2 \rightarrow \Delta Visit_3$	.08 (.29)
$Duration_3 \rightarrow \Delta Visit_4$	.06 (1.55)

Note. *N* = 52. Entries in the table's lower portion are parameter estimates with associated critical ratios (CRs) in parentheses. Salient CRs greater than 1.96 appear in bold. Visit = frequency of visiting *Weather Story*; Duration = duration per visit to Weather Story; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; CI = confidence interval; $Visit_{t-1} \rightarrow \Delta Duration_t$ = latent score of Visit predicting subsequent latent difference score of Duration; $Duration_{t-1} \rightarrow \Delta Visit_t$ = latent scores of Duration predicting subsequent latent difference score of Visit.

Results of the bivariate LDS model including only the non-push group showed that the chi-square value was 67.47, with 17 degrees of freedom and an associated probability of .00. CFI and TLI were not good (.53 and .22, respectively). RMSEA and SRMR were high (.239 and .167, respectively). Overall, the model did not fit the data.

Lastly, Table 23 presents results of the model including *only the push group* and the association between habit strength for overall visitation and frequency of visits.

Table 23 *Bivariate Latent Difference Score Model for Frequency of Visiting and Duration per Visit to Weather Story for Push Group*

Fit indices		
χ^2/df	24.57/17	
CFI	.94	
TLI	.91	
RMSEA	.084 (90% CI = .000 - .152)	
SRMR	.098	
Parameter estimates	*Visit*	*Duration*
Initial status means	13.60 (**16.09**)	25.85 (**14.14**)
Initial status variances	36.64 (**4.52**)	91.26 (**2.47**)
Change means	5.46 (**2.31**)	17.57 (**3.87**)
Change variances	32.16 (**3.62**)	91.26 (**2.47**)
Initial status with constant change	16.14 (**2.34**)	97.28 (**2.58**)
Visit - Duration association		
$Visit_1 \rightarrow \Delta Duration_2$	.09 (.03)	
$Visit_2 \rightarrow \Delta Duration_3$	.06 (.16)	
$Visit_3 \rightarrow \Delta Duration_4$	.06 (.14)	
$Duration_1 \rightarrow \Delta Visit_2$	.09 (.97)	
$Duration_2 \rightarrow \Delta Visit_3$	.15 (1.36)	
$Duration_3 \rightarrow \Delta Visit_4$	.10 (1.05)	

Note. N = 63. Entries in the table's lower portion are parameter estimates with associated critical ratios (CRs) in parentheses. Salient CRs greater than 1.96 appear in bold. Visit = frequency of visiting *Weather Story*; Duration = duration per visit to Weather Story; CFI = comparative fit index; TLI = Tucker-Lewis index; RMSEA = root mean square error of approximation; CI = confidence interval; $\text{Visit}_{t-1} \rightarrow \Delta\text{Duration}_t$ = latent score of Visit predicting subsequent latent difference score of Duration; $\text{Duration}_{t-1} \rightarrow \Delta\text{Visit}_t$ = latent scores of Duration predicting subsequent latent difference score of Visit.

Results of the bivariate LDS model including only the push group showed that the chi-square value was 24.57, with 17 degrees of freedom and an associated probability of .10. CFI and TLI were good (.94 and .91, respectively). RMSEA and SRMR were .084 and .098, respectively. Overall, the model fit was acceptable. The parameter estimates between frequency of visitation and duration per visit to *Weather Story* were not significant. Thus, there was no significant association between frequency of visitation and duration in this study.

DISCUSSION

In the quest to deepen the understanding of the mechanisms underlying media habits, this dissertation proposed that push notifications, as external media prompts, would affect habit formation, and subsequently, that higher habit strength would cause increased usage. To test the effect of push notifications and the association between habit and usage, this dissertation developed a simple weather forecast mobile application called *Weather Story* and asked participants to use it for 20 days and complete a survey every five days, which formed the basis for the three latent difference scores on each variable. Participants were assigned either a condition receiving push notifications every day or another condition receiving no push notification alerts. From the survey data and application log file data, this dissertation explored changes in habit strength for visitation, frequency of visits, and duration of application use.

Contrary to suggestions that push notifications would influence habit formation and habit strength would cause usage, the findings were that receiving push notification alerts on smartphones had no effect on users' evaluation of their habit strength but did have a direct effect on frequency of visits to the mobile application. Prior habit strength for using a similar application predicted the initial habit strength of using the application.

Preliminary analyses for usage behaviors and habits provided a blueprint of results for this dissertation. First, the log file data showed steep negative slopes in frequency of visits, especially between Time 1 and Time 2 for both the push group and non-push group (see Figure 10). In other words, users visited the application more frequently in the beginning. This possibly indicates the users' learning period to master the functions and features of the application. Afterwards, the visits tapered off eventually to only once per day (average frequency of visits for five days). Duration on application use showed mixed patterns, especially for users who did not receive push notification alerts (see Figure 11). For the non-push group, the log file data showed a steep negative slope in duration between Time 1 and Time 2, but increasing at Time 3. Afterwards, it decreased again. For the push group who received push notification alerts, duration of application use decreased between Time 1 and Time 2, barely changed between Time 2 and Time 3, and decreased between Time 3 and Time 4 again.

Second, survey data showed constant growth in habit strength for overall visitation for the non-push group and the growth rate decreased over time (see Figure 8). For the push group, habit strength for overall visitation increased between Time 1 and Time 2 but decreased between Time 2 and Time 3. Afterwards, it increased again.

Results of the univariate LGC model showed that habit strength for overall visitation significantly changed over time for both the push group and non-push group. However, results of a repeated-measures ANOVA indicated that there was no significant difference in habit strength between the two groups. Results indicated that the treatment of push notifications failed. However, as the log data showed, average response time to notifications became shorter for participants who clicked push notifications. This shorter response time suggests the possible effect of push notification on habit formation even though, unfortunately, the study did not show the full process of habit formation.

Regarding the association between habit and usage, this dissertation predicted habit strength for application visitation would increase frequency of visits and duration on application use, based on the assertion of insufficient self-regulation results in increased media consumption (LaRose & Eastin, 2004). Contrary to what was expected, results of the bivariate LDS models did not show a clear association between habit and usage. Results of the bivariate LDS models for the association between habit strength for overall visitation and frequency of visits and duration on application use did not fit the data. The estimated parameters in the models including both users who received push notification alerts and who did not receive push notification alerts showed contradicting results to the hypotheses of this dissertation. Habit strength for overall visitation did not predict frequency of visits although it did negatively influence the duration of application use. It seems that the association between habit and usage differed depending on the condition of either receiving push notifications or not.

Results of the bivariate LDS models for each group did not support the hypothesized effect of receiving push notifications. Results found different directions in the estimated parameters between habit and usage. For users who did not receive push notifications, habit strength for overall visitation at Time 1 positively predicted subsequent change in frequency of visits (see Table 16). For users who received push notification alerts, habit strength for overall visitation at Time 1 negatively predicted subsequent change in frequency of visits (see Table 17). For users who did not receive push notifications, habit strength for overall visitation at Time 2 positively predicted subsequent change in duration on the application, but no significant association was found for users who received push notifications.

Contrary to what was expected, associations between habit and usage were not clearly revealed. The question then becomes, what is the reason for the poor model fits for the associations in this study? Whether users visited the application periodically, repeatedly, or, perhaps, at consistent intervals is worthy of consideration. The application usage data, however, did not show such patterns. Both the push group and non-push group visited the application at random times; there was no specific pattern of visiting throughout the day. Delivered push notification alerts did not determine when users visited the application and habit was not mutually related to specific times of the day (Lally et al., 2010). Moreover, for those who had prior experience in using a weather application, their habit strength for visiting *Weather Story* did not reach a level as high as their prior habit strength for visiting a weather application. Following Lally et al. (2010), it is likely that 20 days was not long enough to establish stable habits. In Lally's study, the media time for participants who were either eating fruit with lunch, drinking water with lunch, or running before dinner to reach 95% of asymptote (i.e., stable scores in habit strength) was 66 days, with a range from 18 to 254 days. Habit strength for overall visitation across four time points did not reach a level as high as an existing habit for visiting a weather application, but it correlated with the existing habit.

However, users' visiting frequency consistently decreased over time but the duration using the application changed corresponding to weather change. Between March 31st and April 1st, the duration of using the application increased at Time 3 when the temperature dropped and there were significant new weather events (e.g., rain or snow) that were significant. Alternatively, the strange behavior change may be attributable to another event during Time 3. During that time, the university's beloved basketball team fell out of the NCAA basketball tournament. This could have changed users' weather application habit in unpredictable ways including disrupting a wide range of routine activities encompassing mobile phone usage behaviors or conversely making weather application visits more salient for some users who were planning basketball tournament related activities outside. This increased duration of application use may reflect controlled or conscious behavior.

Previous studies show a positive relationship between habit and media use, but this study's findings contradict those findings. The direction of change in application use, both frequency of visits and duration on application use, were negative in this study, where mobile application use decreased over time. This finding suggests that habits do not always correspond to an increase in behavior. A possible explanation for this may be related to the content of the mobile application (updating weather information). In particular, *Weather Story* provided a daily summary of weather information for the whole day. Barring unexpected or abrupt weather changes, checking weather information once a day would suffice for most users.

Besides testing the association between habit and usage, this dissertation examined the effect of push notifications on habit formation and usage. The expected differences in habit growth between users who did and did not receive push notifications were based on the question of whether push notifications as a media prompt are more salient as well as active cues that lead to application use (i.e., visits), as compared to other external cues such as location, people, or time. In a comparison across groups of users who did or did not receive push, results of a repeated-measures ANOVA for habit strength of overall visitation were not different between the two groups. Meanwhile, there was a significant group difference in frequency of visits; users who received push notifications visited the application more frequently than those who did not receive push notifications, and the patterns of visiting behavior between two groups were the same. Duration per visit to the application was not different between the two groups. Thus, push notifications had no significant effect on habit strength for overall application visits or duration on application use. However, a significant effect was observed on frequency of visits in this study.

From testing the effects of push notifications on habits and usage behaviors, this dissertation did not find a direct association between habit strength and application usage behaviors, contrary to previous studies of media use, but it did find an effect of push notification on usage behavior, especially frequency of visits. What do these findings explain then? Although habit strength scores were not significantly different between users who received push notifications and those who did not receive them, users who received notifications visited the application more frequently than those who did not. This finding supports Fogg's behavior model (2009) in a very general sense, suggesting the role of triggers in performing behavior. The time to use *Weather Story* was not fixed for the participants, meaning that they visited the application at random times (i.e., when they wanted to use, needed to use, or automatically used), but the number of visitations reached once a day. However, users who received push notifications visited more than those who did not receive notifications. Perhaps participants in both groups had the same level of motivation and ability to use the application but the presence of triggers, push notifications, created additional usage behavior for push notification receivers. However, the puzzling patterns of declining frequency of use and the anomalous duration of visitation observed for the non-push group at T3 cannot be accounted for by Fogg's model. Indeed, it is not possible to determine exactly where push notifications fit in that model due to its confounding lack of conceptual definitions.

Although this finding cannot explain the causation between usage and habits, it supports a potential effect of push notifications as being a salient external cues that increase usage behavior. According to stimuli-response (S-R)/reinforcement theory, behaviors are elicited by some antecedent stimuli (Yin & Knowlton, 2006). The stimulus-behavior association is reinforced when the consequences of the behaviors are satisfactory and, in turn, people perform the behavior when there are the stimuli without cognitive process to respond to the stimuli. Users who received push notifications received new and novel information (i.e., temperature change and chances of rain or snow) via push notification alerts in an efficient and timely fashion. Therefore, it might follow that users would develop an association between push notifications and new and novel information through repeatedly responding to push notifications, thereby increasing the likelihood of developing a habit of using mobile applications through such notifications. Thus, even though habit strength for overall visitation did not reveal the effect of push notifications in this study, the findings showed that users who received push notifications may have experienced an association between push notifications and application visitation during the study period and visited the application more frequently than users who did not receive push notifications, reflecting a potential effect of push notifications on habit strength.

How users responded to push notifications, such as their visitation, is another consideration. Among the 63 push group participants, 32 clicked the push notifications at least once (range from 1 to 19) and 31 participants had no record of clicking push notifications. The average response latency was about 3.98 minutes (*SD* = 8.45). Even though push notifications were delivered with a sound or a buzz, the log file data showed that push notification clickers did not respond to the notifications right away. Rather, they used the application at times other than when they received push notifications. In terms of time, there was no apparent pattern of when participants clicked the push notifications.

Another possible explanation is the technology-mediated interruption management approach, which suggests that people consider the value of information when they experience technology-mediated interruption (e.g., receiving push notifications) as well as context (e.g., mental workload, time, and locations). Users evaluate the value of information and decide whether to accept the interruption or not (Grandihi & Jones, 2010). In this respect, the value of weather information used in this dissertation might not be high enough to compel users to respond to push notification interruptions. However, users came back to push notification messages later and visited the application through push notifications. The significant differences on frequency of visits between push notification clickers and non-clickers as well as between the push group and non-push group, support the effects of push notifications as a reminder.

In conclusion, the present research tells little about the establishment and activation of habits and the associations between habits and usage behaviors. However, it contains several contributions to media habits literature by providing useful insights into the early development of habits, including factors that may influence the attempts of application designers to achieve routine use. First, the findings themselves are informative for future research. Push notifications had a potential effect on frequent use and, in turn, habit growth. Significant differences in frequency of visits between push notification clickers and non-clickers as well as between the push group and non-push group support the effect of push notifications. However, push notification alerts did not lead to immediate actions like launching the application, but may have functioned as a reminder leading to actions later. Future researchers, therefore, would do well to test what explains this latency. In addition, it is worth examining whether the value of information in push notifications changes habit growth, responding actions, and application use behaviors.

In addition, this dissertation found the effect of prior habit on habit formation and growth. Prior experience can be a proxy for habits. For instance, In TPB literature, the frequency of past behavior is used as a measure of habit strength (e.g., Ouelette & Wood, 1998). TAM and UTAUT models also demonstrated that prior experience in using similar technology influences intention to use new technology. In this study, almost 86% of participants were using a weather forecast application. Prior habit strength was strong but habit strength for visiting *Weather Story* did not reach the level of strength as high as users' prior habit strength. Habit strength for *Weather Story* was influenced by prior habit strength over time. This may reflect the impact of an existing habit for using a weather application or simply the fact that, in this study, the present manipulation was ineffective and users never established a habit. Moreover, in this study, *Weather Story* is the same type of application as other weather forecast applications. However, the findings regarding the effect of prior habit strength on habit strength contradict Peters' (2009) study, which demonstrated that prior mobile phone usage experience did not predict habit strength or prospective habit strength for using mobile video phone. Future studies should explore the effect of existing habit strength on new or similar types of application use or other media use.

In addition, this dissertation found an association between frequency of visits and habit strength even though the casual directions were opposite to what was expected. A possible explanation for this contradictory result is that this study entailed the early stage of habit formation. Future research should continue to explore the growth patterns of media habits and change in the association between habit and media use with longer time frames.

In retrospect, a weather application was perhaps not the best choice to test habit formation, at least not over a short period of time during a season in which weather is unstable and when users may habitually use other weather applications. If an application provides information that is more time sensitive, valuable, novel, or otherwise more enticing to individuals, checking frequency and duration using the application would increase with habit strength. Social networking sites or email provide the most common examples where checking once a day is not enough. People seek information and content from social networking sites or emails and other "important" sources deemed by the user more often and with more varied expected outcomes compared to receiving weather forecast updates via an application. For example, it is probably more rewarding to receive a personal email from a friend or receive comments on a Facebook posting than to receive an impersonal update that it will rain or shine this afternoon. When we see individuals' media usage behavior over time, their behaviors may increase, decrease, or become asymptotic depending on the content they access. Thus, content and the value of information to the user determine the level of habit performance in media use by reflecting on individuals' motivations, expected outcomes, emotions, mental conditions, and the effect of "flow" (see Tokunaga, 2013). In this respect, more empirical studies including various types of application and information are needed to not only explore how media habits are formed in different ways but also to better test whether the content and nature of information affects the association between habit strength and media use.

A second contribution of this dissertation concerns the findings of differences between frequency of visits and duration on application use as indicators of mobile application use. Contrary to what was expected, frequency of visits and duration on application use were not correlated with each other. Results of this study showed that duration on application use was more sensitive to weather change or perhaps other external events than frequency of visits. While frequency of visits had significant association with habit strength for visiting through push notifications, duration of using the application did not. This finding explains why previous studies testing mobile phone use measured the number of times a subject used a mobile phone (Peters, 2007, 2009; Soror et al., 2012). Those studies measured the number of times subjects used a mobile phone or ordinal measures for frequency of use to test the relationship between habit and mobile phone use. Here, frequency of visits and duration on the application were different indicators of application use and, thus, related to different factors influencing and deciding behaviors. These results can be explained by the process of habit formation, otherwise described as a shift from goal-directed action to S-R automatic behavior. It is likely that duration of using the application is a better indicator of goal-directed action, whereas checking frequency may be an indicator of S-R automatic behavior. However, Peters' (2009) study used the number of times users used their mobile phone as a measurement of usage and found that habit predicted mobile phone use but expected outcomes did not.

Information-seeking style is another possible explanation for the difference between frequency and duration in media use, particularly supporting why duration was not influenced by push notifications. Information-seeking research suggests that information seeking behaviors vary with many different factors such as motivations and personalities (e.g., Heinstrom, 2005, Weiler, 2005). For example, users with low motivation do "fast surfing" and, in turn, do not search and spend much time in using media for information seeking. Users with openness, curiosity, and creativity do "broad scanning" and "deep diver" search information with a deep strategic approach (Heinstrom, 2005). These types of users probably spend more time than fast surfers in media use. Findings from previous studies support that duration is more likely influenced by motivation, types of content, and ability to use media than by external cues and triggers.

Third, methodologically, this study empirically introduced and examined the effects of push notifications on habit formation and activation. Although this approach ultimately failed to introduce a new habit, the mobile application providing a push notification service enabled the creation, control, and use of this very tool to collect data and examine its role as part of the subject of the research. Future experiments may benefit from the design of this study by having longer periods of observation and using new types of applications that are less influenced by prior habits.

The results of this study should be interpreted cautiously. Despite a longitudinal design and an analytical approach that can support causal inferences, the author cannot definitively conclude that media habits cause media use since it did not control possible confounding factors such as physical location, events, or people. The participants might misunderstand the meaning of "using" the application. Rather than opening the application, using the application may have meant glancing at the notification, which may have provided the only information that was useful to them. Moreover, this study did not provide sufficient data points to detect true growth patterns of habit strengths for application usage. Also, the push group included significantly more iOS users than the non-push group. However, all configurations of *Weather Story* for iOS and Android versions were the same and there was no significant effect of operation system on habit growth or application usage behavior. Further, missing data may alter the results. This dissertation provided results using full information maximum likelihood (FIML) to estimate missing data points, but fewer missing data would provide more accurate results. It seems that the initial size of the panels was not large enough to cover the dropout rates. Future research should continue to explore the growth patterns of media habits using both longitudinal designs that cover extended time frames and robust experimental designs with large sample sizes.

A second limitation is the low response rate in recruiting participants. Although the researcher sent out recruiting message to 24,000 students, the response rate was lower than 1%. Also, there were 50 drop outs. A possible reason for low response rate is perceived intensity of work. The recruiting message indicated that participants were asked to use an application for 20 days and complete four surveys. Students who received this message might feel an excessive burden of commitment. Another possible reason is low compensation. However, higher rewards would be unlikely to attract people to participate in the study since cash incentives of over $10 have diminishing returns (Dillman, 2011). Future research should pay attention to recruiting methods and compensation to get more quality data.

A third potential limitation is the generalizability of this research to other samples and other mobile applications. This sample was only composed of college students, who, as a group, may display different levels of mobile application use compared to the general population, and for whom weather information provided via the application may not be as important as it might to other demographics. There are indications that such differences exist. A 2010 survey conducted by the University of Colorado Boulder found that college students used mobile phones, especially smartphones, while multitasking such as using applications while listening to music, watching TV, and shopping (Dean, 2010). Moreover, according to the Pew Research Center's Internet & American Life Project in 2010, college students, particularly undergraduate students, were more likely to use mobile phones to access the Internet or email than the overall adult population in the survey (63% of undergraduate students versus 41% of all adults (Pew Research Center, 2010). Consequently, the results reported in this dissertation should not be generalized to other types of smartphone applications and information or to other demographic groups. In this respect, future studies should test the role of importance of information with more and different types of smartphone application user groups.

APPENDICES

APPENDIX A

Pretest Questionnaire

1. Please decide your preferred **user ID** for this research and enter it into the text box below. You need to remember your ID and keep using it throughout your participation in this research. You will be asked to enter your user ID when you install the application on your smartphone after the initial meeting with the researcher. Instead of your personal information (e.g., your name, email address, phone number, etc.), this user ID will be used to match your application usage on the application and the surveys you are going to complete. Thus, your privacy can be protected.

2. Are you familiar with mobile weather forecast applications?

Not at all						Very much
1	2	3	4	5	6	7

3. Are you interested in using a mobile weather forecast application?

Not at all						Very much
1	2	3	4	5	6	7

4. Are you using any mobile weather forecast application now (e.g., The Weather Channel, Weatherbug, Go Weather, AccuWeather, etc.)?

Yes/No

5. Please indicate how much you agree or disagree with following statements about your weather forecast application that you are using now. (Response scale: 1 Strongly disagree to 11 Strongly agree)

1) Using the weather forecast application has become a habit for me.
2) I don’t even think twice before using the weather forecast application.
3) Using the weather forecast application is part of my usual routine.
4) I use the weather forecast application without really thinking about it.

Main Questionnaire

1. Please enter your ID number

2. Please indicate how much you agree or disagree with following statements about your **Weather Story** application usage. (Response scale: 1 Strongly disagree to 11 Strongly agree)

1) Using the **Weather Story** application has become a habit for me.
2) I don't even think twice before using the **Weather Story** application.
3) Using the **Weather Story** application is part of my usual routine.
4) I use the **Weather Story** application without really thinking about it.

-Additional questions to push group

5) **Clicking through the push notifications from Weather Story** has become a habit for me.
6) I don't even think twice before **clicking through the push notifications from Weather Story**.
7) **Clicking through the push notifications from Weather Story** is part of my usual routine.
8) I **click through the push notifications from Weather Story** without really thinking about it.

3. What is your gender?

Male/Female

4. What is your year of birth?

5. What is your ethnicity? Please check all that apply:

- Black or African American
- White (Not Hispanic/Not Latino)
- Hispanic or Latino
- American Indian
- Asian
- Native Hawaiian or Pacific Islander
- Multiracial (Having parents of more than one race)
- Member of race not listed above

6. For how long have you been using the current smartphone? (e.g., If you have been using your phone since November in 2012, your answer should be 5 months. Or if you have been using your phone since April 2012, you answer should be 12 months)

APPENDIX B

Recruitment ad – Email version

Title: You are invited to our study about a new smartphone application usage, cash compensation

Dear Students:

Do you own an iPhone or Android phone? I am looking for volunteers to participate in a very simple app evaluation task.

The study title is A Field Trial of a Smartphone Weather App.
The purpose of study is to learn more about how people use smartphone applications.

To participate in this study, you should have a smartphone (e.g. iPhone or Android phone).

Your participation would include:

1. Meeting the researcher in the Cyber Café in the MSU main library to install a new application in your smartphone.
2. Using the application for 20 days.
3. Completing four short questionnaires (each takes only 2-3 minutes)
4. If you complete the survey, you will get $5 per each questionnaire for a total of $20 as our appreciation

***Potential benefits & Risks**
This study is not expected to yield any immediate benefit apart from the weather reports you will have access to. However, there are no obvious physical, legal or economic risks associated with participating in this study. However, you will be asked questions about yourself and these questions can sometimes make people uncomfortable. You do not have to answer any questions that you do not wish to answer.

If you are interested and need further information, please contact Mijung Kim to smartappresearch@gmail.com

Cordially,

Mijung Kim

Ph.D. Candidate

Telecommunication, Information Studies, & Media
Media & Information Studies
Michigan State University

REFERENCES

REFERENCES

Agarwal. R., & Prasad, J. (1997). The role of innovation characteristics and perceived voluntariness in the acceptance of information technologies. *Decision Sciences*, *28*(3), 557-582. doi: 10.1111/j.1540-5915.1997.tb01322.x

Agarwal., R., & Prasad., J. (1999). Are individual differences germane to the acceptance of new information technologies?. *Decision Sciences, 30*(2), 362-391. doi: 10.1111/j.1540-5915.1999.tb01614.x

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes, 50*(2), 179-211. doi: 10.1016/0749-5978(91)90020-T

Ajzen, I. (1996). *The theory of planned behavior: A bibliography.* Unpublished manuscript, University of Massachusetts at Amherst.

Ajzen, I. (2002). Residual effects of past on later behavior: Habituation and reasoned action perspectives. *Personality and Social Psychology, 6*(2), 107-122. doi: 10.1207/S15327957PSPR0602_02

Ally, M., & Gardiner, M. (2012). The moderating influence of device characteristics and usage on user acceptance of Smart Mobile Devices. In *ACIS 2012: Location, location, location: Proceedings of the 23rd Australasian Conference on Information Systems 2012* (pp. 1-11). ACIS/Deakin University.

Bandura, A. (1986). *Social foundations of thought and action: A Social cognitive theory,* Englewood Cliffs, NJ: Prentice Hall.

Bandura, A. (2001). Social cognitive theory: An agentic perspective. *Annual Review of Psychology, 52*(1), 1-26. doi: 10.1146/annurev.psych.52.1.1

Bargh, J. A. (1994). The four horsemen of automaticity: Awareness, efficiency, intention, and control in social cognition. In R. S. Wyer, Jr., & T. K. Srull (Eds.), Handbook of social cognition (2nd ed., pp. 1-40), Hillsdale, NJ: Erlbaum.

Bargh, J. A., & Ferguson, M. J. (2000). Beyond Behaviorism: On the automaticity of higher mental processes. *Psychological Bulletin, 126*(6), 925-945. doi: 10.1037/0033-2909.126.6.925

Barkhuus, L. & Dey, A. (2003). Is context-aware computing taking control away from the user? Three levels of interactivity examined. In *Proceedings of the Fifth Annual Conference on Ubiquitous Computing* (pp.149-156). Berlin Heidelberg: Springer

Barnes, G. M., Reifman, A. S., Farrell, M. P., & Dintcheff, B. A. (2000). The effects of parenting on the development of adolescent alcohol misuse: A six-wave latent growth model. *Journal of Marriage and Family, 62*(1), 175-186. doi: 10.1111/j.1741-3737.2000.00175.x

Bianchi. A., & Phillips, J. G. (2005). Psychological predictors of problem mobile phone use. *CyberPsychology & Behavior*, 8, 39–51. doi: 10.1089/cpb.2005.8.39

Billieux, J. (2012). Problematic use of the mobile phone: A literature review and a pathways model. *Current Psychiatry Reviews*, *8*(4), 299-307. doi: 10.1089/cpb.2005.8.39

Billieux, J., Van der Linden, M., & Rochat, L. (2008). The role of impulsivity in actual and problematic use of the mobile phone. *Applied Cognitive Psychology, 22*(9), 1195-1210. doi: 10.1002/acp.1429

Billieux, J., Van der Linden, M., d'Acremont, M., Ceschi, G., & Zermatten, A. (2007). Does impulsivity relate to perceived dependence on and actual use of the mobile phone?. Applied Cognitive Psychology, 21(4), 527-537. doi: 10.1002/acp.1289

Butt, S., & Phillips J. G. (2008). Personality and self reported mobile phone use. *Computers in Human Behavior, 24*(2), 346-360. doi: 10.1016/j.chb.2007.01.019

Campbell, M. A. (2005). The impact of the mobile phone on young people’s social life. In *Proceedings Social Change in the 21st Century Conference*, Queensland University of Technology Carseldine, Brisbane. Retrieved from http://eprints.qut.edu.au/archive/00003492/

Caplan, S. E. (2002). Problematic Internet use and psychosocial well-being: Development of a theory-based cognitive-behavioral measurement instrument. *Computers in Human Behavior, 18*(5), 553-575. doi: 10.1016/S0747-5632(02)00004-3

Caplan, S. E. (2003). Preference for online social interaction: A theory of problematic Internet use and psychosocial well-being. *Communication Research*, *30*(6), 625-648. doi: 10.1177/0093650203257842

Carlsson, C., Carlsson, J., Hyvönen, K., Puhakainen, J., & Walden, P. (2006). Adoption of Mobile Devices/Services—Searching for Answers with the UTAUT. In *Proceedings of the 39th Annual Hawaii International Conference on System Sciences*, 2006

Cerami, E. (1998). *In delivering push*. New York: McGraw-Hill.

Cheung, C. M. K., & Limayen, M. (2005). The role of habit in information system continuance: Examining the evolving relationship between intention and usage. In *Proceedings of the 26th International Conference on Information Systems*, D. Avison, D. Galletta, & J. I. DeGross (Eds.), Las Vegas, NV, December 11-14, 471-482.

Chittaranjan, G., Blom, J., & Gatica-Perez, D. (2011). Who's who with Big-Five: Analyzing and classifying personality traits with smartphones. In *Proceedings of IEEE International Symposium on Wearable Computers (ISWC)*, San Francisco.

Collins, L. M, Schafer, J.L., & Kam, C.M. (2001). A comparison of inclusive and restrictive strategies in modern missing data procedures. *Structural Equation Modeling, 6*, 330-351. doi: 10.1037/1082-989X.6.4.330

Curran, P., Harford, T., & Muthén, B. (1996). The relation between heavy alcohol use and bar patronage: A latent growth model. *Journal of Studies on Alcohol and Drugs, 57*(4), 410-418.

Curran, P., Obeidat, K., & Losardo, D. (2010). Twelve frequently asked questions about growth curve modeling. *Journal of Cognition and Development, 11*(2), 121-136. doi: 10.1080/15248371003699969

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology, *MIS Quarterly, 13*, 319-339.

Davis, R. A. (2001). A cognitive-behavioral model of pathological Internet use. *Computers in Human Behavior, 17*(2), 187-195. doi: 10.1016/S0747-5632(00)00041-8

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied social Psychology, 22*(14), 1111-1132. doi: 10.1111/j.1559-1816.1992.tb00945.x

Dillman, D. A. (2011). *Mail and Internet surveys: The tailored design method--2007 Update with new Internet, visual, and mixed-mode guide*. John Wiley & Sons.

Drews, F. A., Yazdani, H., Godfrey, C. N., Cooper, J. M., & Strayer, D. L. (2009). Text messaging during simulated driving. Human Factors: The Journal of the Human Factors and Ergonomics Society, 51(5), 762-770. doi: 10.1177/0018720809353319

Duncan, T. E., Duncan, S. C., & Stoolmiller, M. (1994). Modeling developmental processes using latent growth structural equation methodology. *Applied Psychological Measurement, 18,* 343-354. doi: 10.1177/014662169401800405

Edmunds. A., & Morris, A. (2000). The problem of information overload in business organizations: A review of the literature. *International Journal of Information Management*, *20*, 17-28. doi: 10.1016/S0268-4012(99)00051-1

Fischer, J. E., Yee, N., Bellotti, V., Good, N., Benford, S., & Greenhalgh, C. (2010). Effects of content and time of delivery on receptivity to mobile interruptions. In *Proceedings of the 12th international conference on Human computer interaction with mobile devices and services* (pp. 103-112). ACM.

Fishbein, M. & Azjen, I. (1975). *Belief, Attitude, intention and behavior: An introduction to theory and research*. Boston: Addison-Wesley.

Finkel, S. E. (1995). *Causal analysis with panel data*, Beverly Hills: Sage Publication.

Fogg, B. J. (2009a, April). A behavior model for persuasive design. In *Proceedings of the 4th international Conference on Persuasive Technology* (p. 40). ACM.

Fogg, B. J. (2009b, April). The behavior grid: 35 ways behavior can change. In *Proceedings of the 4th international Conference on Persuasive Technology* (p. 42). ACM.

Geser, H. (2004). *Towards a sociological theory of the mobile phone. Sociology in Switzerland: Sociology of the Mobile Phone*. Retrieved from http://www.socio.ch/mobile/t_geser1.htm

Girden, E. (1992). *ANOVA: Repeated measures*. Newbury Park, CA: Sage.

Governors Highway Safety Association (2013). *Distracted driving laws*. Retrieved from http://www.ghsa.org/html/stateinfo/laws/cellphone_laws.html

Graham, J. W. (2003). Adding missing-data-relevant variables to FIML-based structural equation models. *Structural Equation Modeling, 10,* 80-100. doi: 10.1207/S15328007SEM1001_4

Grandhi, S. & Jones, Q. (2010). Technology-mediated interruption management. *International Journal of Human-Computer Studies, 68(2010)*, 288-306. doi: 10.1016/j.ijhcs.2009.12.005

Graybiel, A. M. (2008). Habits, rituals, and the evaluative brain. Annual Review of Neuroscience, 31(1), 359-387. doi: 10.1146/annurev.neuro.29.051605.112851

Guinea, A. O. & Markus, M. L. (2009). Why break the habit of a lifetime? Rethinking the roles of intention, habit, and emotion in continuing information technology use. *MIS Quarterly, 33(3),* 433-444.

Heinström, J. (2005). Fast surfing, broad scanning and deep diving: The influence of personality and study approach on students' information-seeking behavior. *Journal of documentation*, *61*(2), 228-247.

Hosking, S. G., Young, K. L., & Regan, M. A. (2009). The effects of text messaging on young drivers. *Human Factors, 51*(4), 582-592. doi: 10.1177/0018720809341575

Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*, 1-55. doi: 10.1080/10705519909540118

Hull, C.L. (1943). *Principles of behavior: An introduction to behavior theory*. New York: Appleton-Century-Crofts.

Hur, M. H. (2006). Demographic, habitual, and socioeconomic determinants of Internet addiction disorder: An empirical study of Korean teenagers. *Cyberpsychology & behavior, 9*(5), 514-525. doi: 10.1089/cpb.2006.9.514

International Telecommunication Union (2013). *The World in 2013: ICT facts and figures*. Retrieved from: http://www.itu.int/en/ITU-D/Statistics/Documents/facts/ICTFactsFigures2013.pdf

Jenaro, C., Flores, N., Comez-Vela, M., Gonzalez-Gil, F., & Caballo, C. (2007). Problematic Internet and cell-phone use: Psychological, behavioral, and health correlates. *Addiction Research and Theory*, *15*(3), 309-320. doi: 10.1080/16066350701350247

Jenny Dean (2010). *Smartphone user survey: A glimpse into the mobile lives of college students*. Retrieved from http://testkitchen.colorado.edu/reports/smartphone/smartphone-survey/

Ji, M., & Wood, W. (2007). Purchase and consumption habits: Not necessarily what you intend. *Journal of consumer psychology, 17*(4), 261-276. doi: 10.1016/S1057-7408(07)70037-2

Kang, Y. M., Cho, C., & Lee, S. (2011). Analysis of factors affecting the adoption of smartphones. In *Proceedings of the Technology Management Conference, 2011* (pp. 919-925). IEEEE International.

Kanny, D. A. (2005). Cross-lagged panel design. In B. S. Everitt & D. C. Howell (Eds.), *Encyclopedia of Statistics in Behavioral Science* (pp. 450-451). New York: Wiley.

Kim, B. (2012). The diffusion of mobile data services and applications: Exploring the role of habit and its antecedents. *Telecommunications Policy, 36,* 69-81. doi: 10.1016/j.telpol.2011.11.011

Kim, J., LaRose, R., & Peng, W. (2009). Loneliness as the cause and the effect of problematic Internet use: The relationship between Internet use and psychological well-being. *CyberPsychology & Behavior, 12*(4), 451-455. doi: 10.1089/cpb.2008.0327

Kircher, A., Vogel, K., Tornros, J., Bolling, A., Nilsson, L., Patten, C., Malmstrom, T., Ceci, R. (2004). *Mobile telephone simulator study*. Linkoping, Sweden: Swedish National Road and Transport Research Institute. Retrieved from: http://www.cellphonefreedriving.ca/media/VTI_Mbl_sim_report_2004_M969A.pdf

Koo, H. (2010). Cell phone addiction in high school students and its predictors. *Child Health Nursing Research. 16*(3), 203-210.

Kwon, H. S., & Chidambaram, L. (2000, January). A test of the technology acceptance model: The case of cellular telephone adoption. In *Proceedings of the 33rd Annual Hawaii International Conference on System Sciences* (pp. 1023). IEEE Computer Society.

Lally, P., Jaarsveld, C. H., Potts, H. W., & Wardle, J. (2010). How are habits formed: Modeling habit formation in the real world. *European Journal of Social Psychology, 40,* 998-1009. doi: 10.1002/ejsp.674

LaRose, R. (2010). The problem of media habits. *Communication Theory, 20*(2010), 194-222. doi: 10.1111/j.1468-2885.2010.01360.x

LaRose, R. (2013). The psychology of interactive media habits.

LaRose, R., & Eastin, M. S. (2004). A social cognitive theory of Internet uses and gratifications: Toward a new model of media attendance. *Journal of Broadcasting and Electronic Media, 48*, 358-377. doi: 10.1207/s15506878jobem4803_2

LaRose, R., Kim, J. H., & Peng, W. (2010). Social networking: addictive, compulsive, problematic, or just another media habit? In Z. Pappacharissi (Ed.), *A Networked self: Identity Community, and Culture on Social Network Sites* (pp. 59-81). NY: Routledge.

LaRose, R., Lin, C. A., & Eastin, M. S. (2003). Unregulated Internet usage: Addiction, habit, or deficient self-regulation? *Media Psychology, 5(3),* 225-253.

LaRose, R., Mastro, D., & Eastin, M.S. (2001). Understanding Internet usage – A social-cognitive approach to uses and gratifications. *Social Science Computer Review, 19,* 395-413. doi: 10.1177/089443930101900401

Lee, D., & LaRose, R. (2007). A socio-cognitive model of video game usage. *Journal of Broadcasting & Electronic Media*, 51(4), 632-650. doi: 10.1080/08838150701626511

Leung, L., & Wei, R. (2000). More than just talk on the move: Uses and gratifications of the cellular phone. *Journalism and Mass Communication Quarterly*, *77*(2), 308–320. doi: 10.1177/107769900007700206

Li, D. (2007). *Why do you blog: A uses-and-gratifications inquiry into bloggers' motivations.* Paper presented at the annual meeting of International Communication Association, San Francisco, CA.

Limayem, M., Hirt, S. G., & Cheung, C. M. K. (2007). How habit limits the predictive power of intention: The case of information systems continuance. *Management Information Systems Quarterly*, *31*(4), 705–737.

Markus, M. L. (2005). The Technology Shaping Effects of e-Collaboration Technologies—Bugs and Features. *International Journal of e-Collaboration*, *1*(1), 1-23. doi: 10.4018/jec.2005010101

Markus, M. L., & Silver, M. S. (2008). A Foundation for the Study of IT Effects: A New Look at DeSanctis and Poole's Concepts of Structural Features and Spirit. *Journal of the Association for Information Systems*, *9*(10), 609-632.

Marlatt, G. A., Baer, J. S., Donnovan, D. M., & Kivlahan, D. R. (1988). Addictive behaviors: Etiology and treatment. *Annual Review of Psychology*, *39*, 223-252. doi: 10.1146/annurev.ps.39.020188.001255

McArdle, J. J., & Hamagami, F. (2001). Latent difference score structural models for linear dynamic analyses with incomplete longitudinal data. In L. Collins & A. Sayer (Eds.), New methods for the analysis of change (pp. 137–175). Washington, DC: American Psychological Association.

McEvoy, S. P., Stevenson, M. R., & Woodward, M. (2006). The impact of driver distraction on road safety: Results from a representative survey in two Australian states. Injury Prevention, 12, 242-247. doi: 10.1136/ip.2006.012336

Movemofitness (2012, February 14th). How to create a habit: A summary of the Fogg behavioral model in MoveMe – Motivation & Habit Building. Retrieved from http://movemofitness.com/2012/02/how-to-create-a-habit-a-summary-of-the-fogg-behavioral-model/

Neal, D. T., Wood, W., Labrecque, J. S., & Lally, P. (2011). How do habits guide behavior? Perceived and actual triggers of habits in daily life. *Journal of Experimental Social Psychology* (2011), doi:10.1016/j.jesp.2011.10.011

Neal, D. T., Wood, W., Wu, M., & Kurlander, D. (2011). The pull of the past: When do habits persist despite conflict with motives?. *Personality and Social Psychology Bulletin, 37*(11), 1428-1437. doi: 10.1177/0146167211419863

Newell, J. (2003). *The role of habit in the selection of electronic media*. Doctoral dissertation, Michigan State University.

Nielsen (2012). *State of the appnation – A year of change and growth in U.S. smartphones*. Retrieved from http://www.nielsen.com/us/en/newswire/2012/state-of-the-appnation-%C3%A2%C2%80%C2%93-a-year-of-change-and-growth-in-u-s-smartphones.html

Nielsen (2013). *Mobile majority: U.S. Smartphone ownership tops 60%*. Retrieved from http://www.nielsen.com/us/en/newswire/2013/mobile-majority--u-s--smartphone-ownership-tops-60-.html

Ouellette, J.A. (1996). *How to measure habit? Subjective experience and past behavior*. Doctoral dissertation, Texas A&M University.

Ouellette, J. A., & Wood, W. (1998). Habit and intention in everyday life: The multiple processes by which past behaviour predicts future behaviour. *Psychological Bulletin, 124*(1), 54–74. doi: 10.1037/0033-2909.124.1.54

Oulasvirta, A., Rattenbury, T., Ma, L., & Raita, E. (2012). Habits make smartphone use more pervasive. *Personal and Ubiquitous Computing, 16*(1), 105-114. doi: 10.1007/s00779-011-0412-2

Ozcan, Y. Z., & Kocak, A. (2003). Research note: A need or a status symbol?: Use of cellular telephones in Turkey. *European Journal of Communication, 18*(2), 241-254. doi: 10.1177/0267323103018002004

Park, W. K. (2005). Mobile phone addiction. In R. Ling and P. E. Pedersen (Eds.) *Mobile Communications: Re-negotiation of the Social Sphere*. (pp. 253-272). London: Springer.

Park, N., Lee, K. M., & Cheong, P. H. (2008). University instructors' acceptance of electronic courseware: An application of the technology acceptance model. *Journal of Computer-Mediated Communication, 13*(2008), 163-186. doi: 10.1111/j.1083-6101.2007.00391.x

Park, J., Yang, S., & Lehto, X. (2007). Adoption of mobile technologies for Chinese consumers. *Journal of Electronic Commerce Research, 8*(3), 196-206.

Pavlov I. P. (1927). *Conditioned reflexes: An investigation of the physiological activation of the cerebral cortex*. London: Oxford Univ. Press.

Perlow, L. A. (2012). *Sleeping with your smartphone: how to break the 24/7 habit and change the way you work*. Boston: Harvard Business Review Press.

Peters, O. (2007).*Social Psychological Determinants of Mobile Communication Technology Use and Adoption: A Comparison of Three Models to Explain and Predict Mobile Communication Technology Behavior*. Doctoral dissertation, University of Twente, The Netherlands.

Peters, O. (2009). A social cognitive perspective on mobile communication technology use and adoption. *Social Science Computer Review, 27*(1), 76-95. doi: 10.1177/0894439308322594

Peters, O., & Allouch, S. B. (2005). Always connected: A longitudinal field study of mobile communication. *Telematics and Informatics, 22*(3), 239-256. doi: 10.1016/j.tele.2004.11.002

Peters, O., Almekinders, J. J., Van Buren, R. L. J., Snippers, R., & Wessels, J. T. J. (2003, May). *Motives for SMS use*. Paper presented at the annual conference of the International Communication Association, San Diego, CA.

Pew Research Center (2010). *College students and technology*. Retrieved from http://www.pewinternet.org/Reports/2011/College-students-and-technology/Report.aspx

Quellette, J. A., & Wood, W. (1998). Habit and intention in everyday life: The multiple processes by which past behavior predicts future behavior. *Psychological bulletin, 124*(1), 54-74. doi: 10.1037/0033-2909.124.1.54

Rubin, A. M. (2002). The uses-and-gratifications perspective of media effects. In Anonymous (Ed.), *Media effects: advances in theory and research* (pp. 525-548). Mahwah, NJ: Lawrence Elbaum Associates.

Rogers, E. (1995). Diffusion of Innovations. New York, NY: Free Press.

Saling, L. L., & Phillips, J. G. (2007). Automatic behavior: Efficient not mindless. *Brain Research Bulletin, 73*(1-3), 1-20. doi: 10.1016/j.brainresbull.2007.02.009

Shaffer, H. J., Hall, M. N., & Vander Bilt, J. (2000). " Computer addiction": a critical consideration. *American Journal of Orthopsychiatry*. *70*(2), 162-168. doi: 10.1037/h0087741

Sheppard, B. H., Hartwick, J., & Warshaw, P. R. (1988). The theory of reasoned action: A meta-analysis of past research with recommendations for modifications and future research. *Journal of Consumer Research, 15*, 352-343.

Soror, A. A., Steelman, Z. R., & Limayem, M. (2012). Discipline yourself before life disciplines you: Deficient self-regulation and mobile phone unregulated use. *2012 45th Hawaii International Conference on System Sciences (HICSS)*, 849-858. doi:10.1109/HICSS.2101.219

Takao, M., Takahashi, S., & Kitamura, M. (2009). Addictive personality and problematic mobile phone use. *CyberPsychology & Behavior, 12*(5), 501-507. doi: 10.1089/cpb.2009.0022

Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. *Information Systems Research, 6*(4), 144-176. doi: 10.1287/isre.6.2.144

Teo, T. S. H., & Pok, S. H. (2003). Adoption of WAP-enabled mobile phones among Internet users. *International Journal of Management Science, 31*, 483-498. doi: 10.1016/j.omega.2003.08.005

Thompson, R. L., Higgins, C. A., & Howell, J. M. (1994). Influence of experience on personal computer utilization: Testing a conceptual model. *Journal of Management Information Systems, 11*(1), 167-187.

Tokunaga, R. S. (2013). Engagement with novel virtual environments: The role of perceived novelty and flow in the development of the deficient self-regulation of Internet use and media habits. Human Communication Research, 13, 365-393. doi: 10.1111/hcre.12008

Tokunaga, R. S. & Rains, S. A. (2010). An evaluation of two characterizations of the relationships between problematic Internet use, time spent using the Internet, and psychosocial problems. *Human Communication Research, 36,* 512-545. doi: 10.1111/j.1468-2958.2010.01386.x

Turkle, S. (2008). Always-on/always-on-you: The tethered self. In Katz J.E (Ed.), *Handbook of Mobile Communication Studies* (pp. 121-137). Cambridge, MA Press: MIT.

Venkatesh, V., & Davis, F. D. (2000). A theoretical extension of the technology acceptance model: Four longitudinal field studies. *Management Science, 46*(2), 186-204. doi: 10.1287/mnsc.46.2.186.11926

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS Quarterly, 27*(3), 425–478.

Venkantesh, V., Thong, J. Y. L., & Xu, X. (2012). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178.

Verkasalo, H., Lopez-Nicolas, C., Molina-Castillo, F. J., & Bouwman, H. (2010). Analysis of users and non-users of smartphone applications. *Telematics and Informatics, 27*(3), 242-255. doi: 10.1016/j.tele.2009.11.001

Verplanken, B. (2006). Beyond frequency: Habit as mental construct. *British Journal of Social Psychology, 45(3)*, 639–656. doi: 10.1348/014466605X49122

Verplanken, B., & Melkevik, O. (2008). Predicting habit: The case of physical exercise. *Psychology of Sport and Exercise, 9,* 15-26. doi: 10.1016/j.psychsport.2007.01.002

Verplanken, B., & Orbell, S. (2002). Reflections on past behavior: A self-report index of habit strength. *Journal of Applied Social Psychology, 33*(6), 1313-1330. doi: 10.1111/j.1559-1816.2003.tb01951.x

Verplanken, B., & Wood, W. (2006). Interventions to break and create consumer habits. *Journal of Public Policy & Marketing, 25*(1), 90-103. doi: 10.1509/jppm.25.1.90

Walsh, S. P., White, K. M., Cox, S., & Young. R. M. (2011). Keeping in constant touch: The predictors of young Australians' mobile phone. *Computers in Human Behavior, 27*(1), 333-342. doi: 10.1016/j.chb.2010.08.011

Walsh, S. P., White, K. M., Hyde, M. K., & Watson, B. (2008). Dialing and driving: Factors influencing intentions to use a mobile phone while driving. *Accident Analysis & Prevention, 40*(6), 1893-1900. doi: 10.1016/j.aap.2008.07.005

Watson, J. B. (1919). *Psychology from the standpoint of a behaviorist*. Philadelphia, PA: Lippincott.

Wei, R. (2008). Motivations for using the mobile phone for mass communications and entertainment. *Telematics and Informatics, 25*(2008), 36-46. doi: 10.1016/j.tele.2006.03.001

Wei, R., & Lo, V. (2006). Staying connected while on the move: Cell phone use and social connectedness. *New Media & Society, 8*(1), 53-72. doi: 10.1177/1461444806059670

Weiler, A. (2005). Information-seeking behavior in Generation Y students: Motivation, critical thinking, and learning theory. *The Journal of Academic Librarianship, 31*(1), 46-53.

White, M. P., Eiser, J. R., & Harris, P. R. (2004). Risk perceptions mobile phone use while driving. *Risk Analysis, 24*(2), 323-334. doi: 10.1111/j.0272-4332.2004.00434.x

Wood, W., & Neal, D. T. (2007). A new look at habits and the habit-goal interface. *Psychological Review, 114*(4), 843-863. doi: 10.1037/0033-295X.114.4.843

Xu, Z., & Zhu, S. (2012). Abusing notification services on smartphones for phishing and spamming. *Proceedings of the 6th USENIX conference on Offensive Technologies, WOOT'12*, USA, 1-11. Paper retrieved from https://www.usenix.org/system/files/conference/woot12/woot12-final7.pdf

Yin, H. H., & Knowlton, B. J. (2006). The role of the basal ganglia in habit formation. *Nature Reviews. Neuroscience*, *7*(6), 464-476. doi: 10.1038/nrn1919

Young, K. S. (1998). Internet addiction: The emergence of a new clinical disorder. Cyber *Psychology & Behavior*, *1(3)*, 237-244. doi:10.1089/cpb.1998.1.237.

Zakaria, N. (2003). Push technologies: the favorable future communication technology. *4th Annual Multimedia Systems, Electronics, and Computer Science. University of South Hampton.*