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RESEARCH PAPER

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Mobile Health (mHealth) Channel Preference: An Integrated Perspective of Approach-Avoidance Beliefs and Regulatory Focus

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Abstract

It has been suggested that the mobile health (mHealth) channel is effective in assisting with chronic disease management. However, little is known about the mHealth channel preferences of consumers who may be vulnerable to chronic disease. Integrating the lens of approach-avoidance beliefs with regulatory focus theory, we: (1) focus on *mHealth channel preference* (CHANNEL) as our dependent variable, (2) identify *perceived mHealth usefulness* (PU) as an approach belief and *perceived mHealth risk* (RISK) as an avoidance belief, and (3) develop hypotheses pertaining to the how the regulatory focus of the individual (operationalized as *perceived vulnerability to chronic disease*, i.e., VULN) moderates the impacts of PU and RISK on CHANNEL. Based on analyses using structural equation modeling of survey data collected from 954 individuals in the US, we find that, compared to a promotion regulatory focus (low VULN), a prevention regulatory focus (high VULN) *amplifies* the effect of RISK on CHANNEL and *suppresses* the effect of PU on CHANNEL. We discuss the implications of our findings for theory, practice, and future research related to mHealth channel preferences.

Keywords: Mobile Health (mHealth), Approach-Avoidance, Regulatory Focus, Regulatory Fit, Channel Preference, Perceived Vulnerability, Chronic Disease.

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1 Introduction

Health care consumers who traditionally had to visit health care providers in person for all health care services now face an interesting alternative to receive health care advice and exchange clinical information with their health care providers through mobile health (mHealth) applications (Figure 1). mHealth is the "use of mobile and wireless devices to improve health outcomes, health care services, and health research" (http://www.himss.org/definitions-mhealth). mHealth has been touted as having "the potential to change every aspect of the health care environment," as it can enable consumers to actively engage in their chronic disease care and can potentially reduce demands on clinicians (Steinhubl, Muse, & Topol, 2013, p. 2396). Chronic disease has been defined as "a long lasting condition that can be controlled, but not cured" (http://cmcd.sph.umich.edu/what-is-chronic-disease.html). According to the CDC, it is "responsible for 7 of 10 deaths each year, and treating people with chronic disease accounts for 86% of [the US's] health care costs" (http://www.cdc.gov/chronicdisease/index.htm).

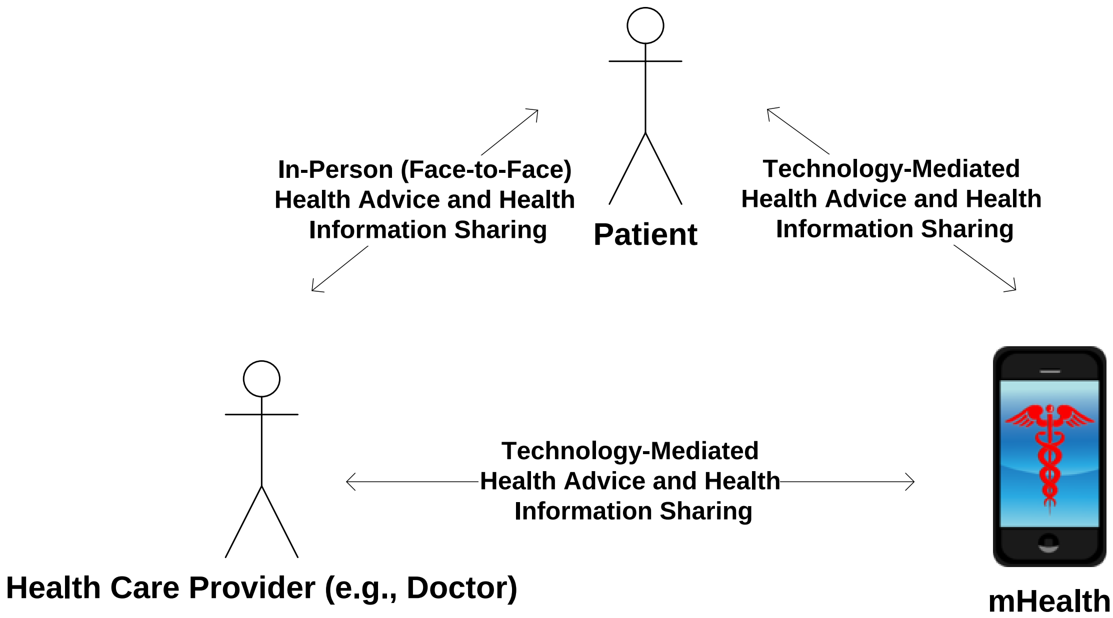


Figure 1. Channel Choices for Health Advice and Health Information Sharing

Chronic diseases such as diabetes and some forms of cardiovascular disease are often attributable, in part, to diet, nutrition, exercise, and behavioral choices such as smoking; as such, chronic incidence can be reduced when such behavioral choices are addressed (Bauer, Briss, Goodman, & Bowman, 2014; Franklin & Pratt, 2016; Kelley, Chiasson, Downey, & Pacaud, 2011). However, making choices that are maximally beneficial to one's individual circumstances, particularly for those vulnerable to chronic disease, often requires health advice and/or information exchange with health care providers.[1] mHealth affords a channel for such clinical advice-seeking and exchange of clinical information with health care providers can enhance the potential of shared decision-making between patients concerned about or actively managing chronic disease and their health care providers (Barry & Edgman-Levitan, 2012). For instance, HealthLoop, Patient IO, and Blue Star are just a few examples of mHealth apps now available to increase engagement and facilitate exchange between patients and their health care providers.[2] Yet, while the use of such apps is increasing, we know little about what motivates health care consumers to consider mHealth as a channel for interacting with health care providers, particularly since such consumers have various technology beliefs and health conditions.

Indeed, research suggests that mHealth can be particularly helpful for addressing chronic concerns and acting as an intermediary in chronic disease management (e.g., Hamine, Gerth-Guyette, Faulx, Green, & Ginsburg, 2015). Chronic disease care is typically information intensive, and mHealth applications afford patients the ability to conveniently receive health advice and share clinical information with their health care providers (Cafazzo, Casselman, Hamming, Katzman, & Palmert, 2012; Steinhubl et al., 2013; Williams, Mostashari, Mertz, Hogin, & Atwal, 2012). However, while interest in mHealth is high and the potential role for it to serve as a channel for health advice and clinical information sharing is certainly present, mHealth usage has been found to be contingent on how health care consumers view their personal vulnerability to chronic disease (Levy, 2012). Further, although past studies have shown that as one's health status deteriorates, the propensity to utilize health services increases, these studies have focused on the utilization of in-person visits involving patients and doctors rather than visits via a technological medium (e.g., Chern, Wan, & Begun, 2002; Connelly, Philbrick, Smith Jr, Kaiser, & Wymer, 1989; Lima & Kopec, 2005). Thus, we are motivated to understand: (1) how mHealth beliefs affect channel preference between mHealth and in-person doctor visits to receive advice and exchange clinical information, and (2) how such impacts are affected by consumers' perceived vulnerability to chronic disease (VULN).

We address these research objectives through the lens of approach and avoidance beliefs (Elliot, 2008; Higgins, 1997) and the interaction of such beliefs with

[1] We use the term "providers" to refer to clinicians, such as doctors and midlevel practitioners, who can provide health advice and health information to consumers.

[2] Source: https://www.beckershospitalreview.com/healthcare-information-technology/50-healthcare-apps-for-clinicians-and-consumers-to-know.html

the regulatory focus of the individual in the technology appraisal processes (Bandura, 2005; Updegraff, Brick, Emanuel, Mintzer, & Sherman, 2015). Although we have learned about how individual factors impact intentions to use technology from prior research in technology acceptance and consumer behavior, we are still limited in our understanding of how preferences for in-person versus technological interactions are constructed in the context of health care. Specifically, we do not yet know enough about how approach beliefs (associated with *perceived mHealth usefulness*, PU) and avoidance beliefs (associated with *perceived mHealth risk*, RISK) are moderated by the regulatory focus of the individual, which places salience on either promotion/gain-framed information or prevention/loss-framed information (associated with *vulnerability to chronic disease*, VULN) in determining consumers' *mHealth channel preferences* (CHANNEL).

In the remainder of this paper, we discuss relevant theoretical background and develop a research model and related hypotheses. We then present details of data collection, analyses, results, including endogeneity and robustness tests, and discussion of implications.

2 Theoretical Background and Hypotheses

We focus on channel preference (CHANNEL), referring to the relative value a consumer places on mHealth (i.e., the technology-mediated service channel) over in-person doctor visits (i.e., the in-person service channel), as our dependent variable. In other words, we focus on the extent to which consumers favor using mHealth rather than in-person doctor visits to seek health advice and exchange clinical information with their health care providers.

Conceptually, we treat the consumer's mHealth channel preference as a decision that can be determined by the extent to which he or she is motivated by approach beliefs associated with approaching positive information versus avoidance beliefs associated with avoiding negative information (Carver & Scheier, 2012; Carver & White, 1994; Elliot & Thrash, 2002; Higgins, 1997). Such beliefs are associated with the regulatory theoretical view of gain-framed individuals, who focus on promotion of desirable situations, and loss-framed individuals, who focus on the prevention of undesirable situations (Higgins, 1998; Updegraff et al., 2015). We expect that consumers' response to approach and avoidance beliefs will differ based on their regulatory focus, because regulatory focus directs people to monitor for and respond to beliefs that fit their regulatory orientation. The health care literature suggests that regulatory focus, with respect to health issues, can be captured by consumers' perceived vulnerability to chronic diseases (Updegraff et al., 2015). Individuals' perceptions of their vulnerability to chronic diseases orient them to be either prevention or promotion focused in terms of their response to information regarding health issues. As such, an individual who perceives high vulnerability to chronic diseases has a prevention-oriented regulatory focus, while someone who perceives low vulnerability is promotion oriented. As summarized below in Table 1, we propose that the impact of technology beliefs on the construction of channel preference will be augmented if the belief fits a consumer's regulatory focus (e.g., prevention-oriented individuals will fit best with a channel that they believe avoids risk) and that the impact will be suppressed if there is a misfit (e.g., promotion-oriented individuals will perceive misfit with a channel that they believe avoids risk, as opposed to one that they believe is useful).

In particular, we focus on theorizing within the context of health care and, specifically, on concerns associated with chronic disease. By doing so, we adopt a contextually focused approach, as it has the potential to generate "context-specific" insights (Hong, Chan, Thong, Chasalow, & Dhillon, 2013). In particular, Johns (2006, 2017) argues that the meaning and interpretation of theoretical relationships are shaped by context and that context may change the functional form, directionality, and strength of relationships.

Table 1. Fit and Misfit between Technology Beliefs and Regulatory Focus

		Technology beliefs	
		Approach beliefs	**Avoidance beliefs**
Regulatory focus	**Promotion-oriented**	***Fit:*** Gain-focused individuals focus on the possibility of positive outcomes.	***Misfit:*** Gain-focused individuals will not be as likely to focus on negative outcomes.
	Prevention-oriented	***Misfit:*** Loss-focused individuals will not be as likely to focus on positive outcomes.	***Fit:*** Loss-focused individuals focus on the possibility of negative outcomes.

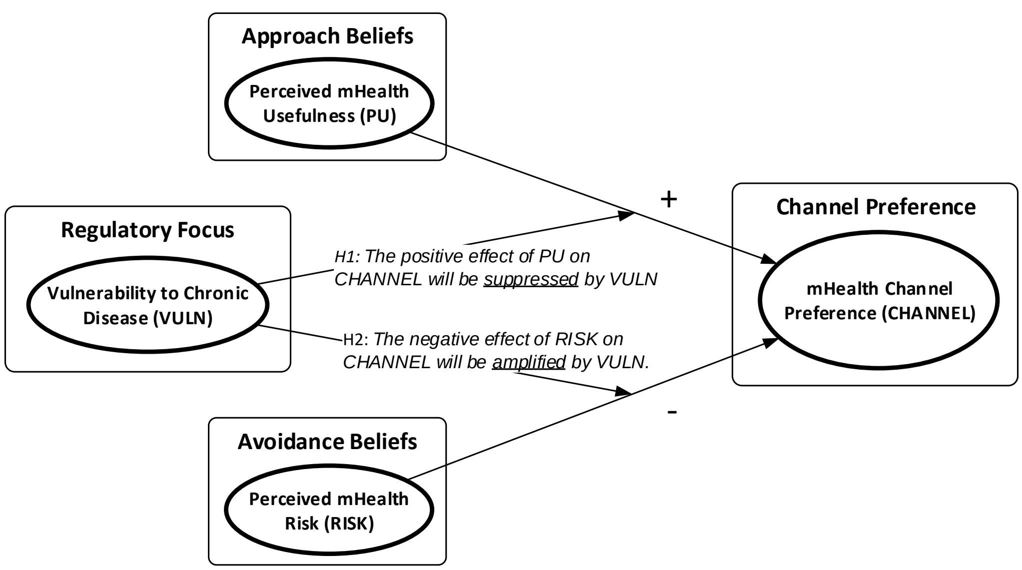
Table 2. Definitions of Concepts and Constructs*

Role	Concept	Concept Definition	Construct	Construct definition	Sources
DV	**Channel preference**	The relative value placed on one service channel over another	mHealth Channel Preference (CHANNEL)	The relative value a consumer places on the mHealth channel over in-person doctor visits.	Muthitacharoen, Gillenson, & Suwan (2006)
IV	**Approach beliefs**	The degree to which one is motivated by approaching positive situations	Perceived mHealth usefulness (PU)	The degree to which a consumer believes use of the mHealth channel will enhance the performance of the health care services.	Davis (1989); Venkatesh, Morris, Davis, & Davis (2003)
IV	**Avoidance beliefs**	The degree to which one is motivated by avoiding negative situations	Perceived mHealth risk (RISK)	The degree to which a consumer believes that the use of the mHealth channel will adversely affect their health.	Bauer (1967); Featherman & Pavlou (2003); Pavlou & Gefen (2005); Taylor (1974)
M	**Regulatory focus**	The cognitive processes that guide the evaluation of information focused on desired outcomes (i.e., promotion oriented) or undesired outcomes (i.e., prevention oriented)	Perceived vulnerability to chronic disease (VULN)	A consumer's self-evaluated probability of becoming a victim of chronic disease.	Bahar (2013); Glanz, Rimer, & Viswanath, (2008); Janz & Becker (1984); Van der Pligt (1998)

Notes:

DV = dependent variable; IV = independent variable; M = moderator

*Following the notion of "ladder of abstraction" (Van de Ven, 2007, p. 115), we make an explicit differentiation between concepts and constructs. Concepts are high-level abstractions that are semantically defined but cannot be operationalized, while constructs are midlevel abstractions that can be operationalized.



Control variables: *Age, gender, education, income, distance to nearest primary care, distance to nearest specialized care, perceived healthiness, subjective norm for mobile services, perceived mHealth ease of use, mobile service use, mHealth adoption decision stage*

Figure 2. Research Model

Accordingly, we define the theoretical constructs in the context of mHealth (see Table 2) and propose a research model (see Figure 2) with two hypotheses to understand the role of regulatory focus in the construction of consumers' channel preferences concerning interactions with health care providers for chronic disease management. Given our contextual focus on chronic disease management, we also control for a number of context-specific variables, detailed in Table 2 and Figure 2, including perceived healthiness and distance to nearest specialty and primary health care providers.

We now (1) elaborate on the conceptualization of our outcome of interest, consumers' preference for the mHealth channel versus the in-person channel (i.e., CHANNEL) for interactions with health care providers related to chronic disease management; (2) summarize the technology-mediated services literature that leads us to focus on PU and RISK as two predictors of CHANNEL; and (3) develop our hypotheses pertaining to the moderating influence of VULN on the impacts of PU and RISK on CHANNEL.

2.1 Conceptualization of mHealth Channel Preference (CHANNEL)

Traditionally, the utilization of health care in the US has been primarily in-person (e.g., ambulatory sick visits, urgent care visits, emergency department visits, and in-patient acute care visits) (Sebelius, Frieden, & Sondik, 2012). However, technology is now providing a viable, convenient, and efficient alternative to such interactions. As of 2015, 64% of US adults owned a smartphone and 62% of these US smartphone owners had used their phone in the past year to "look up information about a health condition" (Smith, 2015). As the mHealth channel provides an alternative to in-person interactions with health care providers, consumers increasingly have significantly more choices concerning the channels they use to interact with health care providers. Thus, understanding why and how consumers develop channel preferences becomes important.

On the one hand, technology-mediated interaction between patients and health care providers is deployed as a possibility for scaling coordination, treatment, and adherence efforts (Beaglehole et al., 2008). On the other hand, uncertainty and fear or concern regarding the impacts of the potential onset of chronic disease and how to effectively manage the symptoms is likely to motivate consumers to consult directly with health care professionals and perhaps doubt the efficacy of self-management (Corbin & Strauss, 1988; Holman & Lorig, 1992) and technology-mediated interaction with health care providers. From a theoretical perspective, technology acceptance research has not focused on the relative preferences between service channels (e.g., Benbasat & Barki, 2007). Rather, such research has focused primarily on consumer use, intentions to use (or purchase), or satisfaction with a given technology as the primary dependent variable (e.g., Brown & Venkatesh, 2005; Brown, Venkatesh, & Bala, 2006; Davis, 1989; Hong, Thong, Wong, & Tam, 2002; Kohli, Devaraj, & Mahmood, 2004; Venkatesh & Bala, 2008; Venkatesh, Brown, Maruping, & Bala, 2008; Venkatesh et al., 2003; Venkatesh, Thong, & Xu, 2012). This has also been the case for a number of studies that have assessed technology acceptance in the context of consumer health information technology (health IT) acceptance (Or & Karsh, 2009). However, another stream of research, the business-to-consumer (B2C) channel preference research stream, has considered channel preference as a dependent variable (e.g., Devaraj, Fan, & Kohli, 2002; Froehle, 2006; Looney, Akbulut, & Poston, 2008; Muthitacharoen et al., 2006). The channel preference construct enables us to capture consumers' preference for a technology-mediated channel (mHealth) over an in-person channel, something not captured by a use or intention-to-use construct of an individual channel.

Thus, we conceptualize CHANNEL as our outcome construct that captures the relative value a consumer places on mHealth (i.e., the technology-mediated service channel) over in-person doctor visits (i.e., the in-person service channel) to receive health advice from or exchange clinical information with health care providers. Prior literature has suggested that situations in which many constraints are in place and autonomy is limited may affect theoretical relationships differently than situations in which fewer constraints are in place and more freedom of choice is available (Hong et al., 2013; Johns, 2006, 2017; Rousseau & Fried, 2001). Accordingly, we theorize CHANNEL with the boundary condition that consumers have a choice between channels for chronic disease management, particularly in terms of seeking health advice and exchanging clinical information with their health care providers.

Unfortunately, conclusive results regarding channel preferences are elusive in the health care context, as many health IT studies have focused on certain patient segments within selected hospital systems and have not considered broader sampling strategies (e.g., Emont, 2011; Hassol et al., 2004). While some clinical studies have begun to assess health outcomes associated with the use of the mHealth channel (e.g., Burke et al., 2012), many such studies take place in specific clinical settings and use mHealth as an intervention or complement to an intervention for a given chronic disease or treatment method (i.e., diabetes). Thus, while the issue of consumer mHealth channel preference is important if the potential of mHealth is to be realized, little is known about what may predict consumer channel preference for mHealth relative to in-person doctor visits.

2.2 mHealth Approach-Avoidance Beliefs and the Role of Perceived Usefulness and Risk

Conceptually, the construction of the preference decision can be influenced by consumers' approach and avoidance beliefs (Carver & Scheier, 2012; Carver & White, 1994; Elliot & Thrash, 2002; Higgins, 1997). In our investigative context, we focus on the role of PU and RISK as approaching and avoiding beliefs, respectively, that influence consumers' preference of mHealth relative to in-person doctor visits.[3]

We select PU as our proxy for approach beliefs because the technology acceptance literature has firmly established PU as a key predictor of technology acceptance when individuals feel positively toward the benefits that using a technology can provide (Davis, 1989; Venkatesh & Davis, 1996; Venkatesh et al., 2003; Venkatesh et al., 2012). We view PU as an approach belief because it reflects consumers' belief in favorable outcomes associated with the use of mHealth (e.g., enhancing the performance of chronic disease management). By contrast, we view RISK as an avoidance belief because it reflects the consumers' belief in unfavorable outcomes associated with the use of mHealth (e.g., adverse effect on their health). In addition to PU and effort (typically assessed as perceived ease of use, which we control for in our models), consumers' risk assessment of the channels available for service use also plays an influential role in affecting consumers' relative channel preferences, as negative feelings can have a suppressing effect on the propensity to accept and use a technology (Bhatnagar, Misra, & Rao, 2000; Chiu, Wang, Fang, & Huang, 2014; Kim, Ferrin, & Rao, 2008; Pavlou, 2003; Van der Heijden, Verhagen, & Creemers, 2003).[4]

Thus, consistent with prior literature, we expect that the mHealth service channel will be preferred only when it is perceived as useful (i.e., will meet or exceed performance expectations) (Davis, 1989; Venkatesh & Davis, 1996; Venkatesh et al., 2003; Venkatesh et al., 2012) and is not perceived as too risky (e.g., Bhatnagar et al., 2000; Chiu et al., 2014; Kim et al., 2008; Pavlou, 2003; Van der Heijden et al., 2003), when controlling for other factors such as perceived mHealth ease of use, subjective norms (with mHealth use), and prior experience with mobile services. In fact, past research across diverse service contexts has shown that these factors are associated with the acceptance of information technology-mediated service delivery (e.g., Devaraj et al., 2002; Froehle, 2006; Montoya-Weiss, Voss, & Grewal, 2003) as well as with acceptance of self-service technologies (e.g., Curran & Meuter, 2005). Our focus is consistent with prior research in mobile banking services (Luo, Li, Zhang, & Shim, 2010) and e-services adoption (Featherman & Pavlou, 2003) that found PU and RISK to be the primary predictors of preferring online services to traditional banking service channels.

2.3 Regulatory Focus and Perceived Vulnerability to Chronic Disease

We further propose that a health care consumer's channel preference regarding approach-avoidance beliefs associated with mHealth appraisals will differ based on the consumer's regulatory focus. The premise of our claim builds on work that shows that behavioral responses to differently framed messages is conditional on an individual's regulatory focus (e.g., Aaker & Lee, 2006; Cesario, Higgins, & Scholer, 2008; Crowe & Higgins, 1997; Higgins, 1998). The health care literature suggests that an individual's high or low perceptions of vulnerability orients them to be prevention or promotion focused with respect to responding to information regarding the health issue (Updegraff et al., 2015). The core idea from this line of work within the health care context is that the fit between the information and regulatory focus affects how an individual perceives health-related behaviors. For instance, a fit between the regulatory focus of health information and the goal-orientation of the individual can result in "*increased strength of engagement* with the goal pursuit process" (italics original) (Cesario et al., 2008, p. 460).

Therefore, taking the constructive processing perspective (Payne, Bettman, & Johnson, 1992), we view the construction of a preference for the mHealth channel as a process of arriving at a channel preference decision affected by the regulatory orientation (promotion-oriented or prevention-oriented, as elaborated below) of the individual. We propose that this process does not merely rely on the cognitive calculative approach to evaluate the information associated with favorable outcomes (i.e., approach beliefs) and unfavorable outcomes (i.e., avoidance beliefs) in order to reach the decision that maximizes utility given the available choice set. Rather, we contend that individuals often use a wide variety of heuristics to simplify the preference construction process (Avnet & Higgins, 2006). The use of heuristics may differ across decision contexts and change the

[3] For the purpose of clarity, we focus on relative preference between two channels (i.e., mHealth and in-person).

[4] Perceived ease of use is also an important predictor, but given that mobile and mHealth applications are now being designed in a "consumer-centric" fashion (see Hoehle & Venkatesh, 2015 for more information about mobile usability), we control for perceived ease of use and do not focus our theory development on it.

importance or weight attached to the selected information. Therefore, an individual's response to information associated with approach and avoidance beliefs will differ based on the selectively attended to and processed information in the specific decision context of the individual.

An important aspect of the decision context is associated with decision makers' regulatory focus. Specifically, people are motivated by two regulatory systems: promotion focus and prevention focus (Higgins, 1997, 1998). Past work has shown that different regulatory systems lead people to monitor for and respond to information with different framings. In the health care context, the literature suggests that consumers' perceptions of their health vulnerability orient them toward different regulatory focuses that determine their response to information regarding health issues (Updegraff et al., 2015). In particular, consumers may have variations in their perceived vulnerability to a broad set of chronic diseases (e.g., cardiovascular disease, cancer, diabetes, high blood pressure, asthma, chronic pain). Addressing vulnerability to a broad set of chronic disease enables us to differentiate whether an individual's regulatory focus regarding their health care is likely to be promotion-oriented (gain focus), as would be expected for those with low vulnerability, or prevention-oriented (loss aversion), as would be expected for those with high vulnerability (Updegraff et al., 2015).

The core idea from this line of work is that an individual's distinct regulatory focus causes the individual to selectively evaluate information related to a choice based on his or her regulatory orientation (e.g., Aaker & Lee, 2006; Cesario et al., 2008). Thus, we propose that the impact of information on preference construction among choices will be augmented when there is a fit between the information and regulatory focus, while the impact will be suppressed when there is a misfit. For instance, prevention-oriented consumers evaluating the health benefits of juice are more likely to be persuaded by advertisements that emphasize antioxidants and cardiovascular disease prevention (i.e., avoidance beliefs in the product), while promotion-oriented consumers are likely to be more attracted to an advertisement that emphasizes vitamin C, energy, and great taste (i.e., approach beliefs in the product) (Aaker & Lee, 2001).

Similar patterns have been observed across other domains, such as oral health (Sherman, Updegraff, & Mann, 2008), HPV vaccination (Gerend & Shepherd, 2007; Nan, 2012), calcium consumption (Gerend & Shepherd, 2013), physical activity (Latimer, Rivers, et al., 2008), fruit and vegetable consumption (Latimer, Williams-Piehota, et al., 2008), and smoking prevention (Zhao & Pechmann, 2007). However, while regulatory focus has been considered with regard to consumer choice (e.g., Avnet & Higgins, 2006), regulatory focus has yet to be applied to channel preferences in health care. This is especially important to consider, as regulatory fit has been shown to reflect consumers' application of beliefs to their health-related decisions (e.g., Hong & Lee, 2007). Thus, if regulatory fit occurs between beliefs (approach vs. avoidance) and regulatory focus (promotion vs. prevention) in health care, consumers may selectively favor beliefs that fit their regulatory orientation in determining their channel preference for health care services. Nevertheless, research has yet to evaluate how regulatory fit influences the impacts of consumers' technology beliefs on channel preferences in interacting with health care providers for chronic disease management.

Along this line of reasoning, we suggest that consumers' high or low *perceptions of vulnerability to chronic diseases* (Bahar, 2013; Frich, Ose, Malterud, & Fugelli, 2006; Glanz et al., 2008; Janz & Becker, 1984; Van der Pligt, 1998; Walter & Emery, 2005) will differentiate how they respond to approach or avoidance beliefs in constructing mHealth preferences. Those perceiving high personal vulnerability will place greater salience on avoidance of mHealth risk, while those perceiving low personal vulnerability will place greater salience on approaching or mHealth usefulness (PU) benefits. We base this reasoning on findings that have shown that people who feel vulnerable to chronic disease are likely to require significant and ongoing advice from health care providers coupled with ongoing health information sharing between patients and providers (Schoen, Osborn, How, Doty, & Peugh, 2009).

It has also been shown that health care utilization increases for people who are confronting a chronic disease or are vulnerable to the onset of a chronic disease and need early interactions with providers (e.g., Agarwal, Gao, DesRoches, & Jha, 2010; Chern et al., 2002; Connelly et al., 1989; Lima & Kopec, 2005). Thus, if consumers perceive themselves to be more vulnerable to chronic disease, they are more likely to perceive an increased need for health services to prevent or address early onset of symptoms. Despite the known influences of PU (increasing) and RISK (decreasing) on consumers' preference for technology-mediated channels across service contexts and the known influence of VULN in increasing the need for and utilization of health care services (pertaining to advice-seeking and clinical information sharing with health care providers), it is unclear how the technology-related predictors PU and RISK interact with the chronic disease-related predictor VULN to affect CHANNEL. Accordingly, we theorize two hypotheses as follows.

First, we expect VULN to suppress the impact of PU on CHANNEL. When consumers perceive themselves as highly vulnerable to a chronic disease, they tend to be prevention-focused concerning their health. These consumers are likely to be especially vigilant against the possibility of negative health outcomes (Higgins, 1997). While PU reflects a belief in the favorable outcomes (i.e., enhancing the performance of the health care services) of mHealth services relative to in-person doctor visits, this approach-oriented belief does not fit with prevention-oriented self-regulation strategies. Prevention-oriented consumers may thus be less persuaded by the approach belief PU in constructing their channel preference. Thus, we predict that the impact of PU on CHANNEL will be weakened for consumers with high vulnerability.

By contrast, consumers who perceive themselves as not vulnerable to chronic diseases will be more promotion oriented. Promotion-oriented consumers strive to achieve and maintain positive outcomes. These consumers approach their goals with eagerness and are sensitive to the presence or absence of gains. Focusing on the relative advantage of mHealth services, PU captures beliefs that fit with promotion-oriented self-regulation strategies. Thus, promotion-oriented consumers are more likely to attend to and be more persuaded by beliefs that fit with their eagerness to pursue gains. In sum, we anticipate that the impact of PU on CHANNEL will be stronger for consumers with a low level of VULN than for those with a high level of VULN.

H1: The positive effect of PU on CHANNEL will be suppressed by VULN.

In addition, we expect VULN to augment the impact of RISK on CHANNEL. Although previous research has considered the impact of technology risk perceptions on IS use decisions and has found that higher technology risk perceptions typically lead to decreased likelihood of use (e.g., Bhatnagar et al., 2000; Chiu et al., 2014; Kim et al., 2008; Pavlou, 2003; Van der Heijden et al., 2003), such studies have also revealed the importance of integrating usage contexts into assessments of technology risk influence. Additionally, prior research has shown consumers' beliefs pertaining to risk aversion are reference dependent, or, in other words, relative rather than absolute (Tversky & Kahneman, 1991) and also domain specific (i.e., contextual) (Weber, Blais, & Betz, 2002).

In our context, while mHealth use for seeking health advice and exchanging clinical information has significant potential for improving clinical care and patient engagement (Free et al., 2013; Ricciardi, Mostashari, Murphy, Daniel, & Siminerio, 2013), mHealth as a novel channel is subject to considerable uncertainties and potential risks. Several studies and news outlets have noted that the mHealth service sector is in its infancy, is mostly unregulated, and could present patient safety risks if appropriate precautions are not taken (Butler, 2015; Lewis, 2014; Roth, 2014). For instance, a *New England Journal of Medicine* article stated in regard to mHealth use, "A bewildering array of mHealth products can make it difficult for individual patients or physicians to evaluate their quality or utility" (Hamel, Cortez, & Cohen, 2014, p. 372). Further, mHealth is rapidly evolving, which involves experimentation of different resource combinations (drawing from Lusch & Nambisan, 2015; Tiwana, Konsynski, & Bush, 2010). Given such uncertainties and the rapid pace of change, consumers may perceive mHealth as potentially risky, and rightfully so, as clinical research has not yet been able to conclusively establish the effectiveness of mHealth interventions (Free et al., 2013).

With a focus on the potential negative outcomes associated with mHealth relative to in-person doctor visits, RISK captures beliefs regarding potential losses and fits with prevention-oriented self-regulation strategies. Specifically, as VULN increases, consumers are more likely to engage in prevention-oriented rather than promotion-oriented self-regulation. Compared to consumers with low levels of VULN, consumers with high levels of VULN may be more attentive to information that allows them to avoid losses and they will thus likely consider RISK to be more important when evaluating their channel choices. Therefore, the impact of RISK on CHANNEL is expected to be stronger for consumers who are more vulnerable to chronic diseases due to their inclination toward prevention-oriented self-regulation strategies.

H2: The negative effect of RISK on CHANNEL will be amplified by VULN.

3 Methodology

3.1 Data Collection and Sample

To examine our research questions and test our hypotheses, we designed a cross-sectional survey to collect data on US consumers' perceptions of mHealth and mHealth channel preferences. We invited a total of 20 reviewers, including physicians, technologists, researchers, and managers working in or very familiar with the mHealth industry to examine the survey instrument in detail before pilot testing the survey. Although most of the expert feedback indicated that the questions were clear and easy to understand, we made revisions according to their suggestions. Using a market research company, we then conducted a pilot study in which we collected data from 134 consumers and examined the open-ended feedback comments, response patterns, scale reliabilities, correlations, and discriminant and convergent validity. We made a few minor changes based on the open-ended feedback comments to ensure that consumers shared a common understanding on the core constructs in the investigated context.

Table 3. Respondents' Demographic Profile (*N*=954)

Variable	Category	Percentage
Gender	Male	48.0%
	Female	52.0%
Education	Not a high school graduate	1.9%
	High school graduate	17.1%
	Some college, but no degree	29.5%
	Associate's degree	14.2%
	Bachelor's degree	26.9%
	Advanced degree	10.5%
Income	Less than $24,999	33.5%
	25K – $49,999	31.4%
	50K – $74,999	20.4%
	75K – $99,999	8.6%
	More than 100K	6.0%
Adoption decision stage	Has not used mHealth	60.2%
	Has used mHealth	39.8%
	Mean	***SD***
Age	45.22	16.03

Finally, we used the same market research company to conduct a national survey. We closely worked with the company to (1) ensure that the sample represented the US census in terms of age, gender, education, and income; and (2) minimize nonresponse bias. Using the online panel from the market research company, 8,673 invitation emails were sent in five successive waves during a 2-week data collection period. We systematically monitored the demographics of incoming responses in each of the five waves and compared the means of the aggregate demographics to US census distributions. Each participant was provided with a unique passcode to access the online questionnaire. This design protected personal information from unauthorized access and also prevented duplicate responses. Reminder emails were sent to participants to encourage them to complete the survey within the fieldwork period. Institutional Review Board (IRB) approval was obtained prior to survey administration.

We received 1,163 valid responses, yielding a response rate of 13.41%. We removed 209 respondents who indicated that they were "not aware"[5] of mHealth services and used the remaining 954 responses as the final sample for our analyses. We carefully examined the distribution of respondents in our sample and found it to be nationally representative as compared with the distributions reported in the US census. The respondents' demographic profile is summarized in Table 3. The sample was relatively balanced in terms of gender (48.0% male and 52.0% female). The average age was 45.22, ranging from 18 to 86 years old (*SD* = 16.03). Respondents had varying levels of education and individual income, representing reasonable variation in socioeconomic status. There was substantial variance among respondents regarding their perceived level of vulnerability to chronic diseases and 83.6% of respondents reported their current healthiness as neutral or healthy. 60.2% of respondents reported that they have yet not used any mHealth services.

3.2 Measures

Previously validated measures were adapted to the mHealth context (Table 4) and used for data collection (see Appendix A for the main survey). To establish respondents' frame of reference with respect to the mHealth services we focused on, we defined *mHealth* within the survey as: "Clinical health care services individuals can access through mobile devices (e.g., mobile phones, personal digital assistants (PDAs), and tablet computers) to interact with their health care providers to: (1) obtain health advice, and (2) exchange clinical information.

[5] We differentiated between "non-aware" and "non-use" where non-aware represents respondents who were not aware that mHealth services are available and non-use represents awareness that such services are available, but not yet having used mHealth services. Therefore, we control for non-use in our model using an adoption decision stage variable, as explained later, but remove non-aware respondents from our model as their perceptions of usefulness and risk are not yet meaningfully developed and the survey was likely the first time they had been exposed to the mHealth concept.

Table 4. Measures of Constructs

Construct	Measures	Sources
mHealth channel preference (CHANNEL)	• My overall feeling is that… • My overall attitude is that… • My overall preference is that… [1 = *In-person doctor visits are much more favorable to mHealth services to obtain health advice and to exchange clinical information with health care providers,* 7 = *mHealth services are much more favorable to obtain health advice and to exchange clinical information with health care providers*]	Muthitacharoen et al. (2006)
Perceived mHealth usefulness (PU)	• Using mHealth services would enhance the effectiveness of my health care activities. • I would find mHealth services useful in taking care of my health. [1 = *Strongly Disagree*, 7 = *Strongly Agree*]	Venkatesh & Davis (1996)
Perceived mHealth risk (RISK)	• There would be a considerable risk involved in using mHealth services to take care of my health. • There would be a high potential for an adverse impact on my health due to my using mHealth services to take care of my health. • My decision to use mHealth services to take care of my health would be risky. [1 = *Strongly Disagree, 7 = Strongly Agree*]	Pavlou & Gefen (2005)
Perceived vulnerability to chronic disease (VULN)*	• I feel vulnerable to one of the severe chronic diseases (i.e., Diabetes/ Heart Disease/ Cancer/ High Blood Pressure/ Stroke) in the next five years. [1 = *Strongly Disagree*, 7 =*Strongly Agree*]	Glanz et al. (2008); Janz & Becker (1984)

* The multi-item measures for this construct, which were highly correlated with this one-item measure, are explained in Appendix B.

Our dependent variable, CHANNEL, was measured with a three-item 7-point Likert scale. This measure was adapted from the Attitude-Based Preference Scale developed by Muthitacharoen et al. (2006). On this scale, 1 indicates that in-person doctor visits are highly preferred over mHealth, 4 indicates that the respondent is indifferent between in-person doctor visits and mHealth, and 7 indicates that using mHealth is highly preferred over in-person visits with a doctor. In this way, CHANNEL captures relative channel preference.

In regard to the independent variables associated with our two hypotheses, PU was measured using a two-item, seven-point Likert scale adapted from Venkatesh and Davis (1996). RISK was measured using a three-item seven-point Likert scale adapted from Pavlou and Gefen (2005) and adapted toward a focus on mHealth services. Based on the feedback from physicians, technologists, researchers, and consumers in our pretest and pilot test and following recommendations on when to use one-item measures (Bergkvist & Rossiter, 2007; Fuchs & Diamantopoulos, 2009), we chose to adopt a one-item measure for VULN since the measure is concrete and is easily and uniformly understood in this situation as a health psychology construct (Van der Pligt, 1998). Thus, for our purposes, a one-item measure represents an equal predictive validity as a multi-item measure (Bergkvist & Rossiter, 2007) and is considered appropriate for this study. Furthermore, the measure will be used as a moderator and previous studies have indicated that one-item measures are appropriate for moderators (Fuchs & Diamantopoulos, 2009). To empirically validate these assumptions, we conducted an auxiliary survey to evaluate the validity of the one-item measure compared with a multi-item measure of VULN. The one-item measure is highly correlated with the multi-item measure, providing strong support for the appropriateness of using this measure in later analyses (more detail on the auxiliary survey is described in Appendix B). In addition, to reflect the measurement error of VULN, which cannot be estimated with a one-item measure, we conducted sensitivity analysis by varying the reliability of the one-item measure of VULN from 0.7 to 1.0, and the results remained largely consistent.

Demographic information such as age, gender, education, and income was collected for control purposes. To validate the alignment between the sample and our focus on mHealth channel preference in the context of the regulatory focus of respondents, we also measured perceived healthiness to capture consumers' current health conditions using a one-item 7-point Likert scale. Since perceived healthiness specifically assesses a concrete attribute (Bergkvist & Rossiter, 2007), this one-item measure is appropriate for this control variable. We also varied the reliability of this scale from 0.7 to 1.0 and found the results to be robust. In addition, we measured distance to primary care, distance to specialty care, perceived mHealth ease of use, subjective norm for mobile services, and mobile services use history to rule out alternative explanations. Finally, to control for the potential impact of the adoption decision stage, we included a dummy variable, mHealth adoption decision stage (STAGE), as a control variable in our models to test the hypotheses. If the respondent had used mHealth, STAGE was 1; otherwise, STAGE was 0.

4 Analysis and Results

4.1 Descriptive Statistics

Table 5 reports the descriptive statistics and reliability for constructs and correlations. Our respondents reported different levels of VULN from 1 = the least vulnerable (14.5%) to 7 = the most vulnerable (16.9%) (mean = 4.11, *SD* = 2.05). In addition, 83.6% of our respondents self-reported their current health condition as neutral or healthier (equal to or greater than 4 in the scale from 1 = *very unhealthy* to 7 = *very healthy*; mean = 5.37, *SD* = 1.47), indicating our results are generalizable toward healthier consumers who, as we discuss later, are concerned about their vulnerability to chronic disease. We conducted a sensitivity analysis by deleting those that indicated themselves neutral or not healthy (perceived healthiness is equal to or less than 4 in the scale). The results from this sensitivity analysis were robust and consistent with our main analyses. As expected, perceived healthiness was positively associated with income and negatively associated with age and VULN.

Overall, the measures had excellent internal consistency, as the Cronbach's alpha varied from 0.93 to 0.97 and the AVE values were larger than 0.50. Confirmatory factor analysis (CFA) fit statistics show that the measurement model provided a good fit (χ^2/df = 10.10, $p < 0.001$; CFI = 0.906, SRMR = 0.053). The indicator loadings varied from 0.80 to 0.96 and were significant ($p < 0.001$), establishing convergent validity (Anderson & Gerbing, 1988). Discriminant validity was demonstrated, as the variance extracted for each construct was higher than the squared correlations between that construct and other constructs. Furthermore, following procedures by Anderson and Gerbing (1988) and Bagozzi, Yi, and Phillips (1991), we constrained the correlation between each possible pair of constructs, one at a time, to unity and then performed a chi-square test to compare this model to the unconstrained model. In all cases, the chi-square difference was significant, indicating sufficient distinction between the constructs.

4.2 Measurement Invariance Across mHealth Adoption Decision Stages

We examined the measurement invariance of the key constructs across groups at different mHealth adoption decision stages (group 1 = respondents who had not used mHealth; group 2 = mHealth users). Following the procedures suggested by Steenkamp and Baumgartner (1998) and the evaluation criteria developed by Cheung and Rensvold (2002), we performed configural invariance and metric invariance analyses for subgroups. The results reveal strong support for configural and metric invariance between the groups in terms of the adoption decision stage (fitness indices of the configural invariance model: χ^2/df = 2.219, CFI = 0.994, RMSEA = 0.032, SRMR = 0.032; $\Delta CFI_{\text{(configural model – metric model)}} = 0.004$), thereby making it meaningful to pool the data across mHealth adoption decision stages and use STAGE as a control in the analyses.

4.3 Hypotheses Testing

We tested the hypotheses using structural equation modeling (SEM) with AMOS 18. We used the full sample (N = 954) to test the proposed structural model, controlling for consumers' adoption decision stage, current health condition (i.e., perceived healthiness), and other control variables (listed in the notes in the results tables). Overall, the proposed model fit the data appropriately, based on the cutoff criteria for fit indices suggested by Hair et al. (2006). As shown in Table 6, consumers who perceived mHealth as more useful were more likely to prefer mHealth to in-person doctor visits (β_{PU} = 0.270, $p <$ 0.05), while consumers who perceived mHealth as riskier were more likely to prefer in-person doctor visits to mHealth (β_{RISK} = -0.203, $p < 0.01$),[6] which is consistent with extant technology acceptance theory. In addition, we found that VULN significantly moderated the positive relationship between PU and CHANNEL ($\beta_{PU*VULN}$ = -0.191, $p < 0.01$), and the negative relationship between RISK and CHANNEL ($\beta_{RISK*VULN}$ = -0.209, $p < 0.01$).

We plotted the interaction effects following the Aiken and West (1991) guidelines. Figure 3 shows that the impact of PU on CHANNEL is suppressed when consumers perceive themselves to be more vulnerable to chronic disease.

[6] The lowest value in our DV represents preference for the in-person channel while the highest value represents preference for the mHealth channel, as described in Table 4.

Table 5. Descriptive Statistics For The Full Sample (*N*=954)

	Mean	***SD***	α	**1.**	**2.**	**3.**	**4.**	**5.**	**6.**	**7.**	**8.**	**9.**	**10.**	**11.**	**12**	**13.**	**14.**
1. CHANNEL	2.38	1.9	0.97	0.95													
2. PU	4.91	1.55	0.95	0.17^{***}	0.96												
3. RISK	4.29	1.64	0.93	-0.06^{*}	0.21^{***}	0.9											
4. VULN	4.11	2.05	NA	-0.06^{*}	0.25^{***}	0.39^{***}	NA										
5. AGE	45.22	16.03	NA	-0.29^{***}	-0.32^{***}	-0.16^{***}	0.06^{*}	NA									
6. GEN	0.52	0.5	NA	-0.06^{*}	0.02	-0.04	0.03	0.13^{***}	NA								
7. EDU	3.79	1.34	NA	0.05	0.02	-0.04	-0.11^{***}	-0.02	-0.11^{***}	NA							
8. INC	2.22	1.17	NA	0.08^{**}	0.15^{***}	0.14^{***}	0.07^{**}	-0.06^{*}	-0.22^{***}	0.39^{***}	NA						
9. DISPRIM	2.50	0.91	NA	-0.13^{***}	0.03	0.10^{***}	0.22^{***}	0.16^{***}	0.03	-0.03	0.06^{*}	NA					
10. DISSPE	2.65	1.09	NA	-0.10^{***}	0.02	0.05	0.15^{***}	0.18^{***}	0.01	0.04	0.08^{**}	0.61^{***}	NA				
11. HEALTHY	5.37	1.47	NA	-0.01	0.33^{***}	0.22^{***}	-0.17^{***}	-0.22^{***}	-0.04	0.07^{**}	0.28^{***}	-0.03	0.02	NA			
12. SN	4.19	1.93	NA	0.11^{***}	0.55^{***}	0.34^{***}	0.31^{***}	-0.30^{***}	-0.02	0.08^{**}	0.21^{***}	0.07^{**}	0.05	0.34^{***}	NA		
13. PEOU	5.16	1.51	NA	0.11^{***}	0.74^{***}	0.18^{***}	0.17^{***}	-0.28^{***}	0.02	0.04	0.15^{***}	-0.01	0.03	0.32^{***}	0.44^{**}	NA	
14. MOBILEUSE	3.64	0.78	NA	-0.07^{**}	0.04	0.00	-0.02	0.03	0.13^{***}	0.08^{**}	0.10^{***}	0.06^{*}	0.09^{***}	0.15^{***}	0.04	0.09^{***}	NA
15. STAGE	0.40	0.49	NA	0.19^{***}	0.49^{***}	0.27^{***}	0.22^{***}	-0.38^{***}	-0.06^{*}	0.09^{***}	0.26^{***}	0.01	-0.01	0.30^{***}	0.48^{**}	0.41^{***}	0.03

CHANNEL: mHealth channel preference
PU: Perceived mHealth usefulness
RISK: Perceived mHealth risk
VULN: Perceived vulnerability to chronic disease
AGE: Age
GEN: Gender
EDU: Education
STAGE: mHealth adoption decision stage

INC: Income
DISPRIM: Distance to primary care
DISSPE: Distance to specialized care
HEALTHY: Perceived healthiness
SN: Subjective norm for mobile services
PEOU: Perceived mHealth ease of use
MOBILEUSE: Mobile service use history

$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
Cronbach's Alpha

Diagonals represent square root of AVEs, and off-diagonals represent correlations

Table 6. SEM Results (N = 954)

Variable	+ Control variables		+ Main effects		+ Interaction effects	
DV: CHANNEL	**Estimate**	***SE***	**Estimate**	***SE***	**Estimate**	***SE***
AGE	-0.028***	0.004	-0.026***	0.004	-0.027***	0.004
GEN	-0.024	0.117	-0.039	0.115	-0.033	0.114
EDU	0.016	0.046	-0.010	0.046	-0.017	0.046
INC	0.112**	0.057	0.136**	0.056	0.140**	0.056
DISPRIM	-0.215***	0.079	-0.178**	0.079	-0.151*	0.078
DISSPE	0.015	0.066	0.017	0.065	-0.002	0.065
HEALTHY	-0.171***	0.043	-0.200***	0.047	-0.136***	0.049
SN	0.019	0.038	0.040	0.042	0.050	0.041
PEOU	0.033	0.044	-0.059	0.059	-0.018	0.059
MOBILEUSE	0.005***	0.001	0.005***	0.001	0.005***	0.001
STAGE	0.379***	0.143	0.407***	0.145	0.493***	0.146
PU			0.270**	0.110	0.257**	0.110
RISK			-0.203***	0.076	-0.105	0.081
VULN			-0.148**	0.071	-0.097	0.072
PU*VULN					-0.191***	0.068
RISK*VULN					-0.209***	0.070
χ^2/ df	2.264		2.167		2.489	
CFI	0.996		0.993		0.988	
GFI	0.990		0.980		0.967	
NFI	0.993		0.988		0.981	
RMSEA	0.036		0.035		0.040	
SRMR	0.010		0.014		0.014	

CHANNEL: mHealth channel preference
PU: Perceived mHealth usefulness
RISK: Perceived mHealth risk
VULN: Perceived vulnerability to chronic disease
AGE: Age
GEN: Gender
EDU: Education
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
STAGE: mHealth adoption decision stage
INC: Income
DISPRIM: Distance to primary care
DISSPE: Distance to specialized care
HEALTHY: Perceived healthiness
SN: Subjective norm for mobile services
PEOU: Perceived mHealth ease of use
MOBILEUSE: Mobile services use history

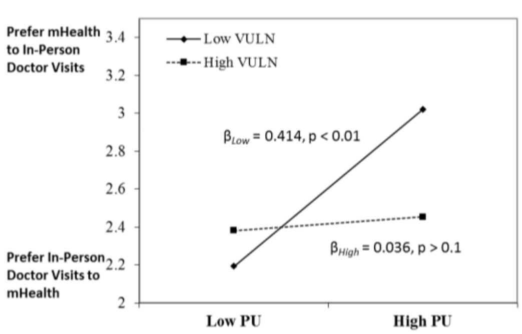


Figure 3. Interaction Effect of VULN and PU

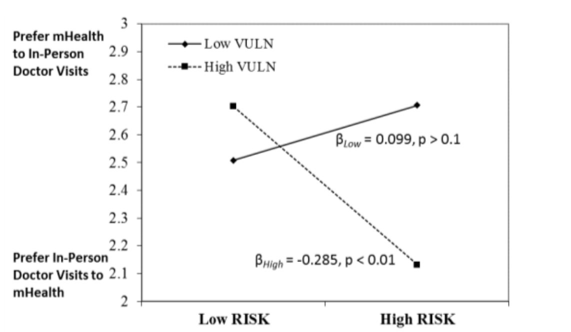


Figure 4. Interaction Effect of VULN and RISK

The results of simple slope tests show that the effect of PU on CHANNEL is significant for consumers with low VULN (β_{Low_VULN} = 0.414, p < 0.01), but not significant for those with high VULN (β_{High_VULN} = 0.036, p > 0.1). In contrast, the impact of RISK on CHANNEL (Figure 4) is amplified when consumers perceive themselves as more vulnerable to chronic diseases. Simple slope test results show the negative effect of RISK on CHANNEL is significant for consumers with high VULN (β_{High_VULN} = -0.285, p < 0.01), but not significant for consumers with low VULN (β_{Low_VULN} = 0.099, p > 0.1).

Among the controls, we found age (AGE), distance to primary care (DISPRIM), and perceived healthiness (HEALTHY) to be significant and negatively associated with CHANNEL. We found income, mobile service use history (MOBILEUSE), and mHealth adoption decision stage (STAGE) to be significant and positively associated with CHANNEL.

To further test the validity of our results, we performed a series of robustness analyses. First, we conducted a subsample analysis by deleting those respondents that indicated their healthiness to be neutral or not healthy (perceived healthiness equal to or less than 4 in the scale from 1 = *very unhealthy* to 7 = *very healthy*). Robustness test results using the healthy subsample were consistent with the results using the full sample (Table 7).

Table 7. SEM Results for Subsample of Healthy Respondents (*N* = 798)

Variable	+ Control variables		+ Main effects		+ Interaction effects	
DV: CHANNEL	Estimate	*SE*	Estimate	*SE*	Estimate	*SE*
AGE	-0.026***	0.005	-0.024***	0.005	-0.025***	0.005
GEN	0.021	0.131	0.009	0.130	0.021	0.129
EDU	0.011	0.051	-0.021	0.052	-0.034	0.052
INC	0.143**	0.061	0.169***	0.061	0.171***	0.061
DISPRIM	-0.301***	0.090	-0.261***	0.090	-0.229**	0.089
DISSPE	0.048	0.074	0.044	0.073	0.017	0.073
HEALTHY	-0.426***	0.088	-0.429***	0.095	-0.289***	0.102
SN	0.039	0.043	0.065	0.047	0.078	0.047
PEOU	0.06	0.053	-0.052	0.073	-0.009	0.073
MOBILEUSE	0.005***	0.001	0.005***	0.001	0.005***	0.001
STAGE	0.388**	0.159	0.410**	0.163	0.486***	0.163
PU			0.294**	0.129	0.220	0.141
RISK			-0.151*	0.091	-0.073	0.103
VULN			-0.177**	0.083	-0.089	0.086
PU*VULN					-0.227**	0.091
RISK*VULN					-0.173*	0.089
χ^2/df	2.053		1.993		3.271	
CFI	0.996		0.994		0.980	
RMSEA	0.036		0.035		0.053	
SRMR	0.010		0.014		0.015	

CHANNEL: mHealth channel preference
PU: Perceived mHealth usefulness
RISK: Perceived mHealth risk
VULN: Perceived vulnerability to chronic disease
AGE: Age
GEN: Gender
EDU: Education
$^{***}p < 0.01$; $^{**}p < 0.05$; $^{*}p < 0.1$
STAGE: mHealth adoption decision stage
INC: Income
DISPRIM: Distance to primary care
DISSPE: Distance to specialized care
HEALTHY: Perceived healthiness
SN: Subjective norm for mobile services
PEOU: Perceived mHealth ease of use
MOBILEUSE: Mobile services use history

Note: Subsample includes only those with HEALTHY > 4 (scale: 1 = *very unhealthy* to 7 = *very healthy*)

Next, we conducted a secondary analysis using ordinary least squares (OLS) using unit means of measurement items as proxies for construct scores (results shown in Table 8). We found: (1) PU was *positively* associated with CHANNEL, (2) RISK was *negatively* associated with CHANNEL, (3) VULN *suppressed* the positive impact of PU on CHANNEL, and (4) VULN *amplified* the negative impact of RISK on CHANNEL. These results were consistent with the SEM results for both the full sample and for the subsample that included only consumers who perceived themselves to be healthy. We conducted a sensitivity analysis by deleting those that indicated their healthiness to be neutral or not healthy (perceived healthiness equal to or less than 4 on 1 = *very unhealthy* to 7 = *very healthy*). Robustness test results using the healthy subsample were consistent with the results using the full sample (Table 8).

Table 8. OLS Results

	Full sample (*N* = 954)		**Subsample (*N* = 798): Perceived healthiness > 4**	
DV: CHANNEL	**Estimate**	***SE***	**Estimate**	***SE***
Constant	2.512^{***}	0.063	2.618^{***}	0.082
AGE	-2.586^{***}	0.372	-2.364^{***}	0.419
GEN	-0.016	0.059	0.007	0.067
EDU	-0.020	0.063	-0.041	0.071
INC	0.169^{**}	0.068	0.207^{***}	0.074
DISPRIM	-0.143^{*}	0.074	-0.219^{***}	0.084
DISSPE	-0.002	0.073	0.021	0.082
HEALTHY	-0.205^{***}	0.073	-0.455^{***}	0.152
SN	0.091	0.076	0.139	0.088
PEOU	-0.018	0.087	-0.008	0.106
MOBILEUSE	2.649^{***}	0.370	2.419^{***}	0.416
STAGE	0.259^{***}	0.073	0.248^{***}	0.082
PU	0.225^{**}	0.095	0.191	0.119
RISK	-0.093	0.069	-0.042	0.086
VULN	-0.095	0.073	-0.092	0.086
PU*VULN	-0.189^{***}	0.062	-0.235^{***}	0.079
RISK*VULN	-0.192^{***}	0.062	-0.145^{*}	0.076

CHANNEL: mHealth channel preference
PU: Perceived mHealth usefulness
RISK: Perceived mHealth risk
VULN: Perceived vulnerability to chronic disease
AGE: Age
GEN: Gender
EDU: Education
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

STAGE: mHealth adoption decision stage
INC: Income
DISPRIM: Distance to primary care
DISSPE: Distance to specialized care
HEALTHY: Perceived healthiness
SN: Subjective norm for mobile services
PEOU: Perceived mHealth ease of use
MOBILEUSE: Mobile services use history

Note: Subsample includes only those with HEALTHY > 4 (scale: 1= *very unhealthy* to 7 = *very healthy*)

4.4 Post Hoc Analyses

4.4.1 Common Method Bias

Although all variables were measured by surveying health care consumers, our findings are not significantly biased by common-method bias. First, as suggested by Podsakoff and Organ (1986), we conducted a Harman's single-factor test. The results show that there was no general factor accounting for more than 50% of the variation. Second, following Podsakoff, MacKenzie, Lee, and Podsakoff (2003), we assessed the measurement model by adding a latent common method variance factor and found that (1) the item loadings and (2) the correlation and covariance coefficients, together with the corresponding significance levels, remained stable between the original measurement model and the measurement model with the common method variance factor. The above evidence collectively suggests that common method bias is not a validity threat in this study.

4.4.2 Assessing mHealth Channel Preference for Specific Activities

We conceptualized and assessed CHANNEL at the level of consumers' overall interactions with health care providers, including activities such as exchanging clinical information and seeking advice from health care providers. In addition to CHANNEL, we measured substitutive use of mHealth with respect to two activities—obtaining health advice (Sub1) and exchanging clinical information (Sub2) (see the measurement items in Appendix A). The two items, corresponding to mHealth use as a substitute for doctor visits for these two activities, are measured on a 7-point Likert scale (1= *Strongly Disagree*, 7 = *Strongly Agree*). We find that CHANNEL is significantly correlated with both Sub1 and Sub2 ($r_{CHANNEL\text{-}Sub1}$= 0.292, $p < 0.01$; $r_{CHANNEL\text{-}Sub2}$ = 0.270, $p < 0.01$); plus, Sub1 and Sub2 are highly correlated ($r_{Sub1\text{-}Sub2}$ = 0.754, $p < 0.01$).

When CHANNEL is replaced with Sub1 and Sub2, respectively, as the dependent variable, the interaction terms PU*VULN and RISK*VULN are significant in the same direction. The results in Table 9 indicate that our findings are consistent with reference to consumers' preference for mHealth use for specific activities (i.e., obtaining health advice and exchanging clinical information).

Table 9. SEM Results for Substitute Use of mHealth (*N* = 954)

	DV: Sub1		DV: Sub2	
DV: CHANNEL	**Estimate**	***SE***	**Estimate**	***SE***
Constant	4.490***	0.226	4.883***	0.212
AGE	-0.203***	0.051	-0.272***	0.048
GEN	0.038	0.092	-0.056	0.086
EDU	-0.010	0.049	0.011	0.046
INC	-0.019	0.052	0.082*	0.049
DISPRIM	0.001	0.057	-0.054	0.053
DISSPE	0.013	0.056	0.066	0.053
HEALTHY	0.021	0.057	-0.033	0.053
SN	0.201***	0.059	0.162***	0.055
PEOU	0.047	0.068	0.114*	0.063
MOBILEUSE	-0.022	0.045	-0.118***	0.042
STAGE	0.441***	0.115	0.183*	0.108
PU	0.872***	0.073	0.925***	0.069
RISK	-0.165***	0.063	-0.005	0.059
VULN	-0.145**	0.056	-0.174***	0.053
PU*VULN	-0.094*	0.048	-0.103**	0.045
RISK*VULN	-0.190***	0.047	-0.169***	0.044

Sub1: Willingness to use mHealth services for obtaining health advice instead of in-person doctor visits
Sub2: Willingness to use mHealth services for exchanging clinical information with health care providers instead of in-person doctor visits
PU: Perceived mHealth usefulness
RISK: Perceived mHealth risk
VULN: Perceived vulnerability to chronic disease
AGE: Age
GEN: Gender
EDU: Education
INC: Income
DISPRIM: Distance to primary care
DISSPE: Distance to specialized care
HEALTHY: Perceived healthiness
SN: Subjective norm for mobile services
PEOU: Perceived mHealth ease of use
MOBILEUSE: Mobile services use history
STAGE: mHealth adoption decision stage

*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$

4.4.3 Addressing Endogeneity

We first evaluated the potential endogeneity caused by the possible impact of VULN on PU and RISK. We used the following two approaches for this assessment: (1) the whole residual approach (Garen, 1984, 1988; Mooi & Ghosh, 2010); and (2) the two-step Heckman analysis originally applied to sample selection, which has also been used to correct for endogeneity in both discrete choice (Heckman, 1979) and continuous choice endogenous variable specifications (Garen, 1984, 1988).

We followed the Carson and John (2013) application of the Garen procedure. In the first-stage regression, we regressed PU on VULN and control variables (i.e., demographic variables, PEOU, SN, and perceived healthiness), and computed the residual for PU (η_{PU}). Similarly, we also regressed RISK on VULN and control variables and computed the residual for RISK (η_{RISK}). We then conducted the standard Durbin-Wu-Hausman Test (Davidson & MacKinnon, 1993) to evaluate whether endogeneity is an issue in our context. Specifically, we used the two residuals (η_{PU} and η_{RISK}) and the two interactions between residuals and the endogenous variables (η_{PU} * PU, η_{RISK} * RISK) as additional regressors in the second-stage regression to predict CHANNEL. The coefficient was significant for η_{RISK} (η_{RISK} = 0.724, $p < 0.01$) but not for η_{PU} (η_{PU} = - 0.278, $p > 0.1$), indicating that RISK is endogenous to VULN. The coefficients for the interactions between residuals and endogenous variables evaluated how PU and RISK behaved over the range of the residuals.

Table 10. Second-Stage Results for the Garen Whole Residual Analysis (Controlling for Endogeneity of PU and RISK to VULN)

DV: CHANNEL	Estimate	*SE*
Constant	2.430***	0.110
AGE	-0.529***	0.077
GEN	-0.022	0.122
EDU	-0.031	0.064
INC	0.202***	0.070
DISPRIM	-0.136*	0.073
DISSPE	0.009	0.073
PEOU	-0.210	0.230
MOBILEUSE	-0.087	0.059
STAGE	0.571***	0.150
VULN	0.236**	0.114
PU	0.604*	0.351
RISK	-0.948***	0.307
PU*VULN	-0.192***	0.062
RISK*VULN	-0.199***	0.061
η_{PU}	-0.278	0.218
η_{RISK}	0.724***	0.268
η_{PU} * VULN	-0.047	0.051
η_{RISK} * VULN	-0.117**	0.057

CHANNEL: mHealth channel preference
PU: Perceived mHealth usefulness
RISK: Perceived mHealth risk
VULN: Perceived vulnerability to chronic disease
AGE: Age
GEN: Gender
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
EDU: Education
INC: Income
DISPRIM: Distance to primary care
DISSPE: Distance to specialized care
PEOU: Perceived mHealth ease of use
STAGE: mHealth adoption decision stage
MOBILEUSE : Mobile services use history

Table 11. Second-Stage Results for the Two-Step Heckman Analysis

	A. Controlling for Endogeneity of PU and RISK to VULN		B. Controlling for Endogeneity of PU and RISK to CHANNEL	
DV: CHANNEL	**Estimate**	***SE***	**Estimate**	***SE***
Constant	5.156***	1.929	-4.377***	0.015
AGE	-0.165	0.221	-0.001**	0.001
GEN	0.211	0.208	-0.001	0.001
EDU	0.151	0.162	0.001***	0.001
INC	0.153**	0.071	-0.001	0.001
DISPRIM	-0.133*	0.073	0.001	0.001
DISSPE	0.013	0.073	-0.001	0.001
HEALTHY	-0.472**	0.199	-0.003***	0.001
SN	0.031	0.097	-0.005***	0.001
PEOU	-0.284	0.258	-0.022***	0.002
MOBILEUSE	-0.084	0.059	-0.001**	0.000
STAGE	0.545***	0.150	-0.003**	0.001
PU	0.223**	0.095	0.000	0.001
RISK	-0.067	0.071	-0.004***	0.001
VULN	-0.984	0.678	-0.002***	0.001
PU * VULN	-0.139**	0.066	-0.002***	0.001
RISK * VULN	-0.124*	0.070	-0.002***	0.001
λ_{PU} (Inverse Mills Ratio)	-0.431	0.362	-0.030***	0.003
λ_{RISK} (Inverse Mills Ratio)	-4.859	3.852	8.589***	0.026

CHANNEL: mHealth channel preference
PU: Perceived mHealth usefulness
RISK: Perceived mHealth risk
VULN: Perceived vulnerability to chronic disease
AGE: Age
GEN: Gender
*** $p < 0.01$; ** $p < 0.05$; * $p < 0.1$
EDU: Education
INC: Income
DISPRIM: Distance to primary care
DISSPE: Distance to specialized care
PEOU: Perceived mHealth ease of use
STAGE: mHealth adoption decision stage
MOBILEUSE : Mobile services use history

As shown in Table 10, after controlling for the endogeneity of PU and RISK to VULN, VULN significantly moderated the relationships between PU and CHANNEL (PU * VULN = -0.192, $p < 0.01$) and between RISK and CHANNEL (RISK * VULN = -0.199, $p < 0.01$).

Next, we conducted a two-step Heckman analysis by following the procedure used by Bharadwaj, Bharadwaj, and Bendoly (2007) and Hsieh, Rai, and Xu (2011). We dichotomized the endogenous variables using a mean split (i.e., individual respondents with scores above the mean coded as 1 and individual respondents with scores at or below the mean coded as 0). We then used the dichotomized endogenous variables, PU_D and RISK_D, as the dependent variables in the first-stage models and used CHANNEL as the dependent variable in the second-stage models. Endogeneity of PU to VULN and RISK to VULN were accounted for by including the inverse Mills ratio from the first-stage regressions (λ_{PU} and λ_{RISK}) in the second-stage regression and then comparing the results to our main analysis results. Our results were robust and largely consistent after controlling for the endogeneity of PU and RISK to VULN, as shown in Table 11 Column A. More specifically, the significance and direction of the coefficients for the interaction terms (PU * VULN and RISK * VULN) are the same as in the previously specified SEM model.

We also evaluated the endogeneity of PU and RISK to CHANNEL using the two-step Heckman analysis. In the first-stage models, we used the dichotomized endogenous variables, PU_D and RISK_D, as the dependent variables and added CHANNEL and control variables as predictors. In the second-stage models, we used CHANNEL as the dependent variable and included inverse Mills ratios for both PU and RISK along with all other predictors. We found that PU and

RISK are endogenous to CHANNEL (λ_{PU} = -0.030, p < 0.01; λ_{RISK} = 8.589, p < 0.01). After accounting for the endogeneity of PU and RISK to CHANNEL, the results are consistent with our previously reported SEM results (Table 11 Column B).

5 Discussion

The implications of our results reveal the importance of considering consumers' regulatory focus with respect to their health vulnerability to chronic diseases in understanding how approach and avoidance beliefs associated with the mHealth channel affect consumers' relative preference of mHealth over in-person doctor visits (Table 13). Our study provides an integrative perspective on how mHealth beliefs, conditional on perceived vulnerability to chronic disease, impact channel preference between mHealth and in-person doctor visits. This study builds upon existing research in the domains of technology acceptance and channel preferences by: (1) taking the lens of approach and avoidance beliefs (i.e., PU and RISK) as a theoretical foundation to explain consumers' channel preference; and (2) integrating the role of consumers' regulatory focus with respect to health issues (i.e., perceived vulnerability to chronic disease) in moderating the effects of approach and avoidance beliefs on channel preference.

Table 13. Interpretation of Findings and Implications

Interpretation of Findings	• The impact of PU on consumers' preference for mHealth is strengthened, yet the impact of RISK is weakened, for consumers who are highly vulnerable to chronic diseases. • Our interpretations are that consumers selectively favor (disfavor) beliefs that fit (misfit) their regulatory orientation in determining their preference for mHealth. • Fit exists when: (1) promotion-oriented consumers (e.g., low VULN) process approach beliefs (e.g., PU), and (2) prevention-oriented consumers (e.g., high VULN) process avoidance beliefs (e.g., RISK). • Misfit exists when: (1) promotion-oriented consumers (e.g., low VULN) process avoidance beliefs (e.g., RISK), and (2) prevention-oriented consumers (e.g., high VULN) process approach beliefs (e.g., PU).
Theoretical Contributions	• Demonstrates that the effects of approach and avoidance beliefs associated with the mHealth channel may be conditional on health-related regulatory focus. The effects will be augmented when an individual's beliefs fit with his/her regulatory focus (e.g., PU for consumers with low VULN; RISK for consumers with high VULN) or suppressed when there is a misfit (e.g., PU for consumers high VULN; RISK for consumers with low VULN). • Implies that an individual's regulatory focus—that is, whether the regulatory focus is promotion- or prevention-oriented with respect to health care services—is a contextualized individual difference that should be considered in assessing the consumers' channel preference. • Suggests an alignment perspective be incorporated into mHealth IS artifacts where the features and content framing are aligned with the promotion or prevention orientation of consumers.
Practical Implications	• Reveals the significant potential of mHealth as a channel in assisting consumers in interacting with their health care providers and exchanging clinical information with them for chronic disease management. • Suggests practitioners need to align the design of technology-mediated health care service channels with consumers' health-related regulatory focus for health advice-seeking and clinical health information exchanging services.

5.1 Implications for Theory

While previous studies have evaluated how regulatory focus and regulatory fit impact consumer decision-making processes and evaluations (e.g., Aaker & Lee, 2006; Avnet & Higgins, 2006; Förster, Grant, Idson, & Higgins, 2001; Hong & Lee, 2007), we are the first, to our knowledge, to consider the important impacts of regulatory focus and regulatory fit on channel preference decisions. Specifically, our results reveal that consumer preferences for mHealth are influenced by their approach and avoidance beliefs associated with the channel. Our results are consistent with past work on technology acceptance (Franklin & Pratt, 2016; Meuter, Ostrom, Roundtree, & Bitner, 2000) and channel preference (Devaraj, Fan, & Kohli, 2006; Kuruzovich, Viswanathan, Agarwal, Gosain, & Weitzman, 2008), but also extend this work by demonstrating that consumer decision-making is more nuanced and regulatory focus is especially critical in the health channel context. Specifically, our results extend prior technology acceptance and channel preference research by surfacing that the nature of channel preference influences is conditional on consumer regulatory focus with respect to health issues—i.e., perceived vulnerability to chronic diseases. The findings demonstrate that consumers selectively favor beliefs that fit their regulatory orientation in determining their preference for mHealth. In particular, fit exists when (1) promotion-oriented consumers (e.g., low VULN) evaluate approach beliefs (e.g., PU) out of a propensity to focus on the possibility of positive outcomes, and (2) prevention-oriented consumers (e.g., high VULN) consider avoidance beliefs (e.g., RISK) out of a propensity to focus on the possibility of negative outcomes. By contrast, misfit exists when (1) promotion-oriented consumers (e.g., low VULN) process avoidance beliefs (e.g., RISK), and (2) prevention-oriented consumers (e.g., high VULN) process approach beliefs (e.g., PU). Our findings suggest that the preference for mHealth is strengthened when fit occurs and weakened when misfit occurs. For example, in the case of consumers with high VULN, whereas the impact of PU on CHANNEL is suppressed because the approach belief does not fit with their prevention orientation, the impact of RISK on CHANNEL is augmented because the avoidance belief fits with their prevention orientation. Collectively, our study suggests that the effects of approach and avoidance beliefs, respectively, will be *augmented* when they fit the consumers' regulatory focus and will be *suppressed* when there is a misfit.

These findings are theoretically significant because they demonstrate that channel preference choices are more nuanced than previously considered, particularly in regard to individual differences in the context in which channel preferences are evaluated. The moderating role of VULN suggests that consumer differences with respect to regulatory focus for health care need to be considered alongside different consumer beliefs related to a channel in order to understand consumer preference for the channel. Further, given that our health care system is moving toward health promotion rather than merely disease management addressing the symptoms and causes of acute diseases (Bandura, 2005), these findings imply that simply providing an alternative channel to in-person interactions will not be sufficient for driving user selection of that channel. Rather, it is likely that the design of the technological artifact being supplied as the alternative will explicitly need to consider how to address promotion versus prevention decision-making orientations within the consumer segment being targeted.

For example, as technological advances provide the opportunity for health care consumers to become more active participants in their care (Payton, Pare, Le Rouge, & Reddy, 2011), health care consumers may be persuaded to use a technology-mediated channel if they are made aware of features of the technology-mediated channels that fit their health-related regulatory focus or if the features are adapted to the promotion or prevention orientation of the individual. As such, our study implies that an alignment perspective is necessary to design effective persuasion mechanisms within IS artifacts: the content focus and feature emphasis within the IS artifact need to be aligned with the likely disposition of consumers in terms of their respective promotion or prevention focus in assessing health services. When dealing with individuals with a promotion orientation, placing salience on the positive outcomes of mHealth for chronic disease management, such as how the mHealth features help enhance the effectiveness of health care activities, will enhance mHealth channel preference. By contrast, when dealing with individuals with a prevention orientation, the mHealth artifact should place salience on mitigating concerns about potential mHealth risks to enhance mHealth channel preference.

Finally, our results affirm the viewpoint that incorporating contextual factors into research questions and models can be a pathway to generate theoretical contributions, because these contextual factors can play a significant role in the direction and magnitude of theoretical relationships (Hong et al., 2013; Rai, 2017). In particular, our work introduces a context-specific construct, VULN, to represent consumers' health-related regulatory focus, an important aspect of individual differences in selective attention likelihood in the health care context. The discovery of the moderating effect of VULN enriches discussions on the determinants of preference for technology-mediated channels used to exchange services. Our findings suggest that an individual's beliefs related to a technology-mediated service channel interact with their regulatory focus—that is, whether it is promotion- or prevention-oriented with respect to the service—to affect their preference for the technology-mediated channel relative to other channels for the service exchange. Further, we control for a number of context-specific sources of variation, including the perceived healthiness of the individual and the individual's distance to primary and specialty care. Overall, our findings support arguments by Johns (2006, 2017) and Hong et al. (2013) suggesting that incorporating contextual factors into explanations of a phenomenon can lead to revisions of explanations and an elaboration in the theoretical understanding of the phenomenon.

5.2 Implications for Practice

Our study also provides insightful implications for practitioners. We suggest that practitioners design technology-mediated service channels that fit with (or adapt to) consumers' health-related regulatory focus. Such design may strengthen consumers' feelings and evaluations of technology-mediated channels (e.g., mHealth) for health advice-seeking and clinical health information exchanging services. Further, while current health policies such as meaningful use mostly focus on technologies like patient portals, questions remain as to how to effectively implement and use additional patient-facing technologies like mHealth, and how to address related factors such as patient uptake and satisfaction associated with such technology use (Ahern, Woods, Lightowler, Finley, & Houston, 2011; Barry & Edgman-Levitan, 2012). Our findings suggest that practitioners and policy makers should widen their considerations beyond just patient portals and carefully consider the significant potential of mHealth. However, in doing so, they should consider how individual differences may impact channel preference decisions and design the technological channel options to align with (or adapt to) such differences.

5.3 Limitations and Opportunities for Future Research

We acknowledge that health care service channels may not be independent of each other. Although consumers might place unequal values on mHealth versus in-person doctor visit channels, they might use these two channels in a complementary or substitutive way for different goals. By definition, channel complementarity is a relationship and pertains to the marginal increases in the impact of a variable on an outcome of interest with increases or decreases in the theorized complementary variable (Milgrom & Roberts, 1995). Channel complementarity is beyond the focus of this study, since we are interested in explaining variance in channel preference as the construct of interest, but it could be of interest in future studies. Specifically, future studies could investigate the complementary or substitutive relationship between the mHealth channel and in-person doctor visits with respect to relevant patient outcomes. In addition, as we limit our focus to an aggregate treatment, based on exchanging clinical information and medical advice for the purpose of chronic disease management, future work could expand to other activities and consider channel complementary with respect to different outcomes.

Second, we adopt the attitude-based approach in order to operationalize CHANNEL in a way that captures the consumers' overall evaluation of the two channels. Alternatively, an attribute-based approach (Muthitacharoen et al., 2006) may be taken by future studies to elaborate consumers' preference formation based on the comparison of specific attributes or health care activities. This approach reveals potential insights into consumers' cognitive processes at a granular level and provides pragmatic values for the industry.

Finally, while this study has contributed to our knowledge of regulatory focus and approach-avoidance beliefs when making channel preference decisions, we did not evaluate whether or not mHealth usage (or usage of the in-person channel), especially under conditions of regulatory fit, affected health-related goal attainment. Prior research has suggested that health care is a particularly fruitful area for evaluating the relationship between regulatory fit and the strength of engagement in goal pursuits (e.g., Cesario et al., 2008; Hong & Lee, 2007). Therefore, while we have extended our understanding of how channel preference decisions are made when a technological alternative is available, future research could extend these findings by evaluating whether or not channel interactions, under conditions of regulatory fit (misfit), positively (negatively) impact goal attainment.

6 Conclusion

We developed an integrative model to explain mHelath channel preference over in-person doctor visits by theorizing how a consumer's approach and avoidance beliefs related to mHealth interact with the consumer's regulatory focus toward health care. We found that the effect of PU on mHealth channel preference is enhanced when a consumer's regulatory focus toward health care is promotion oriented and that the effect of RISK on mHealth channel preference is suppressed when a consumer's regulatory focus toward health care is prevention oriented. We contribute to theory by expanding the understanding of how beliefs concerning a technology-mediated service channel affect preference for the channel (relative to other channels) based on whether the consumer's regulatory focus in relation to the service is promotion or prevention oriented. We provide guidance to practitioners and suggest that health care policy should begin to consider designing and incentivizing mHealth to assist those concerned about chronic disease.

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Appendix A: Questionnaire for the Main Survey

I. Demographic Information:

1. Please indicate your year of birth: ____________
2. Please indicate your gender:
   □ Male □ Female
3. Please indicate the highest level of education obtained.
   □ Not a high school graduate □ High school graduate
   □ Some college, but no degree □ Associate's degree □ Bachelor's degree
   □ Advanced degree
4. Please indicate your individual income per month (before tax).
   □ Less than $24,999 □ $25,000 - $49,999 □ $50,000 - $74,999
   □ $75,000-$99,999 □ More than $100,000
5. Please indicate how close the primary healthcare facilities are from your home.
   □ Less than 1 mile □ 1-5 miles □ 1-10 miles □ Greater than 11 miles
6. Please indicate how close the specialized healthcare facilities are from your home.
   □ Less than 1 mile □ 1-5 miles □ 1-10 miles □ Greater than 11 miles

II. Mobile Services Questions:

7. When did you start using a mobile phone?
   □ Less than 1 year ago □ 1 year-3 years ago □ 3-5 years ago □ More than 5 years ago

8. Please indicate the degree of your agreement with the following statements:

Strongly Disagree	Disagree	Slightly Disagree	Neutral	Slightly Agree	Agree	Strongly Agree
1	2	3	4	5	6	7

People who influence me think that I should use new mobile services.	1	2	3	4	5	6	7
People who are important to me think that I should use new mobile services.	1	2	3	4	5	6	7

III. Health Questions:

9. Please indicate how healthy you feel. I feel I am…

Very Unhealthy	Unhealthy	Somewhat Unhealthy	Not Sure	Somewhat Healthy	Healthy	Very Healthy
1	2	3	4	5	6	7

10. Please indicate the degree of your agreement with the following statement:
    I feel vulnerable to severe chronic diseases (i.e., Diabetes/Heart Disease/Cancer/ High Blood Pressure/Stroke) in the next five years.

Strongly Disagree	Disagree	Slightly Disagree	Neutral	Slightly Agree	Agree	Strongly Agree
1	2	3	4	5	6	7

Definition of mHealth Services:

mHealth services here refers to various clinical healthcare services that individuals can access through mobile devices (e.g., mobile phones, personal digital assistants (PDAs), and tablet computers) that will be useful in health care.

Key mHealth services are:
a. To obtain health advice through mobile devices.
b. To exchange clinical information (e.g., blood pressure, blood sugar, etc.) with healthcare providers through mobile devices.

IV. mHealth Perceptions:

11. Please indicate the degree of your agreement with each item:

Strongly Disagree	Disagree	Slightly Disagree	Neutral	Slightly Agree	Agree	Strongly Agree
1	2	3	4	5	6	7

Using mHealth services would enhance the effectiveness of my health care activities.	1	2	3	4	5	6	7
I would find mHealth services useful in taking care of my health.	1	2	3	4	5	6	7

I would find mHealth services easy to use.	1	2	3	4	5	6	7

There would be a considerable risk involved in using mHealth services to take care of my health.	1	2	3	4	5	6	7
There would be a high potential for an adverse impact on my health due to my using mHealth services to take care of my health.	1	2	3	4	5	6	7
My decision to use mHealth services to take care of my health would be risky.	1	2	3	4	5	6	7

V. mHealth Channel Preference:

12. Please indicate your view on mHealth and in-person doctor visits to obtain health advice and to exchange clinical information with health care providers.

	In-Person Doctor Visits are much more favorable	In-Person Doctor Visits are more favorable	In-Person Doctor Visits are slightly more favorable	Neutral	mHealth Services are slightly more favorable	mHealth Services are more favorable	mHealth Services are much more favorable
My overall feeling is that…	1	2	3	4	5	6	7
My overall attitude is that…	1	2	3	4	5	6	7
My overall preference is that…	1	2	3	4	5	6	7

VI. Substitute Use of mHealth:

13. Please indicate the degree of your agreement with each item.

Strongly Disagree	Disagree	Slightly Disagree	Neutral	Slightly Agree	Agree	Strongly Agree
1	2	3	4	5	6	7

I am willing to use mHeatlh services for obtaining health advice instead of in-person doctor visits	1	2	3	4	5	6	7
I am willing to use mHealth services for exchanging clinical information with health care providers instead of in-person doctor visits	1	2	3	4	5	6	7

Thank you once again for participating in this important study!

Appendix B: The Auxiliary Survey

We conducted an auxiliary survey (see Table B1) to evaluate the validity of the one-item measure of VULN. The results of this survey provide evidence supporting the validity of the one-item measure of VULN. In terms of the procedure, we adapted a five-item measure of VULN from Champion and Scott (1997) and collected participants' demographic information and their responses to the one-item and five-item measures of VULN (see Table B1).

Table B1. The One-Item Measure and Five-Item Measure of VULN (*N*=62)

Item#		Statement	References
1-Item Measure	**SV_1**	I feel vulnerable to severe chronic diseases (e.g., Diabetes/Heart Disease/Cancer/ High Blood Pressure/Stroke) in the next five years.	Glanz et al. (2008); Janz & Becker (1984)
5-Item Measure	**MV_1**	It is extremely likely that I will get severe chronic diseases in the next five years	Champion & Scott (1997)
	MV_2	My chances of getting severe chronic diseases in the next five years are great.	
	MV_3	I feel I will get severe chronic diseases sometime in the next five years.	
	MV_4	Developing severe chronic diseases is a possibility for me in the next five years.	
	MV_5	I am concerned about the likelihood of developing severe chronic diseases in the next five years.	
Scale: 1= *Strongly Disagree*; 7 = *Strongly Agree*			

We administered the online survey to undergraduate and graduate students in the business school of a large public university in the Midwest region of the United States. We sent invitation emails to 128 students and received 62 complete responses during a 2-week data collection period, yielding a response rate of 48.4%.The demographic characteristics of the sample is summarized in Table B2.

Table B2. Respondents' Demographic Profiles

Item#		Frequency	Percentage
Gender	Male	35	56.5%
	Female	27	43.5%
Education	Not a high school graduate	0	0.0%
	High school graduate	4	6.5%
	Some college, but no degree	22	35.5%
	Associate's degree	1	1.6%
	Bachelor's degree	15	24.2%
	Master's degree or above	20	32.3%
Individual Income	Less than $24,999	52	83.9%
	25K - $49,999	2	3.2%
	50K – $74,999	1	1.6%
	75K – $99,999	4	6.5%
	More than 100K	2	3.2%
		Mean	***SD***
Age		25.02	4.68

The results show that the one-item measure of VULN is highly correlated with the average of the multiple items (α = 0.866, $p < 0.001$) and with each of the multi-item measures (see Table B3). These results indicate that the one-item measure has a consistent meaning with the multi-item measure for consumers, thus supporting the validity of the one-item measure that we use in our primary analysis.

Table B3. Correlations between the One-Item Measure and Multi-Item Measure of VULN (*N*=62)

Constructs	1	2	3	4	5
1. SV_1	1				
2. MV_1	.804	1			
3. MV_2	.815	.943	1		
4. MV_3	.827	.947	.969	1	
5. MV_4	.741	.753	.797	.800	1
6. MV_5	.747	.617	.603	.647	.757
Note: All the correlations are significant at the level of $p < 0.001$					

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