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Abstract:

Healthcare providers increasingly rely on technology, such as patient portals, for asynchronous communication with their patients. Even though clinicians have increasingly adopted patient portals to enhance healthcare quality and reduce cost, few patients continue to use this technology. In this paper, we investigate the effect that individuals' health emotion and personality traits as measured using the five-factor model (FFM) have on patients' intention to continually use patient portals through the lens of emotional dissonance theory. We collected survey data from 187 patients at a major medical center in the Midwestern United States. After we analyzed the data using structural equation modeling, we found that the final model explained 40 percent of the variance in intention to continue to use. Our results suggest that whether individuals continue to use technology depends on their reactions to technology in which health emotions and personality traits play a crucial part. Additionally, health emotion modifies the effect that personality traits have on patients' intention to continue to use a patient portal. Our study provides healthcare organizations with an integrated view of patient portal use behavior and shows that individual personality traits and health emotion may increase sustainable patient enrollment and engagement.

Keywords: Health Emotion, Personality Traits, Intention to Continue to Use, Patient Portals, Health Information Technology, Emotional Dissonance Theory.

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1 Introduction

The Health Insurance Portability and Accountability Act of 1996 (HIPAA) requires covered entities (CEs) such as hospitals and physicians to provide patients with access to their protected health information (PHI), which includes both personal and health information, in a secure environment (HHS, 1996). Roughly 90 percent of CEs have adopted patient portals to address this HIPAA requirement (Heath, 2018b). These patient portals constitute an essential component of electronic health record (EHR) systems. Using these portals, patients can view results from tests, schedule appointments, and manage their records. Because these portal allow patients to access their PHI from EHR systems, researchers frequently refer to them as patient gateways (Schnipper et al., 2008), "tethered personal health records" (PHR), or "tethered PHR" (Goel et al., 2011a; Kaelber, Jha, Johnston, Middleton, & Bates, 2008). CEs expect online patient portals to play a critical role in patient care, especially for patients with chronic illnesses such as diabetes, by improving their access to their health information (Sarkar et al., 2010). As the demand for quality healthcare increases, we can expect a global shortage of healthcare facilities and staff, which includes nurses and physicians. To meet such demand, healthcare providers may need to rely increasingly on technology such as patient portals for asynchronous communication with their patients and as a feasible substitute for in-person interactions such as those that occur during physician visits.

Despite patient portals' growing significance in healthcare, few patients adopt the technology (Ancker et al., 2011; Patel, Barker, & Siminerio, 2015). To succeed, any information system relies on the users' sustainably and actually using it (DeLone & McLean 1992; Gaskin, Godfrey, & Vance, 2018; Hung, Tsai, & Chuang, 2014) in a suitable and sufficiently frequent manner (Delone & McLean, 2003; Devaraj & Kohli, 2000). The Office of the National Coordinator for Health Information Technology (ONC) recently noted 52 percent of CEs offered patient portals in 2017 (Patel & Johnson, 2018), which, according to Heath (2018), increased to 90 percent in 2018. While a promising increase, only 30 percent of patients used patient portals in 2018 up from 28 percent in 2017, which makes patient access a significant challenge for healthcare organizations (Heath, 2018a, 2018b). On contrast, 71 percent of U.S. citizens access their online banking account (Board of Governors of the Federal Reserve System, 2016) and 81 percent make purchases online (Clement, 2019). The need to identify the factors that influence users to adopt patient portals and sustainably use these systems remains incredibly important as the ultimate benefits of healthcare organizations' technology adoption depend on the degree to which patients continuously actually use these technologies.

Existing studies on patient portal use have identified factors that may result in low patient engagement, such as a lack of computer access; low computer literacy; and differences in age, race, ethnicity, and education (Ancker et al., 2011; Fowles et al., 2004; Goel et al. 2011a, 2011b; Hsu et al., 2005; Huvila et al., 2018; Li, Gupta, Zhang, & Sarathy, 2014; Nicholas, Huntington, & Williams, 2003; Roblin, Houston, Allison, Joski, & Becker, 2009; Sarkar et al., 2010, 2011; Weingart, Rind, Tofias, & Sands, 2006). While these studies extend our knowledge about the role that demographic factors, socio-economic factors, and individual characteristics in patient portal user behaviors, the existing literature ignores important factors (namely, personality traits and health emotion) in profiling patient portal users.

Studies in health information technology (HIT) use have seldom studied dispositional factors, such as individuals' personality traits. However, other disciplines have studied these factors, such as organizational behavior, education, human psychology, and information systems (IS) adoption (Saleem, Beaudry, & Croteau, 2011). HIT includes all technology used in caring for patients, which includes EHR and patient portals. IS researchers who have examined technology adoption in various contexts have long argued and proved that users' traits such as cognitive styles and personality traits affect their technology use behavior (Bariff & Lusk, 1977; McElroy, Hendrickson, Townsend, & DeMarie, 2007).

Emotions evoke strong feelings about an object, situation, or event. Individuals often use emotion in the decision-making process as a guide to form their judgment capabilities (Clore, Gasper, & Garvin, 2001). Health emotion can play an essential role in whether people continuously use HIT as the technology becomes integrated into their lives. Researchers consider health emotion as an important factor that indicates how severe an individual perceives their immediate health status and plays a vital role in health information-disclosure decisions (Anderson & Agarwal, 2011).

Informed and motivated by existing literature on HIT and technology use, we explore the effect that individuals' health emotions and personality traits have on their intention to continually use patient portals through the lens of emotional dissonance theory. Specifically, we explore three research questions (RQ):

RQ1: Do individuals' health emotions influence their intention to continue to use HIT?

RQ2: Do personality traits play an important role in individuals' intention to continue to use HIT as research has found in non-HIT contexts?

RQ3: Do health emotion and personality traits interact to influence individuals' intention to continue to use HIT?

With this study, we contribute to the literature in four ways. First, we extend the personality traits research model to a healthcare setting. Healthcare digitization has facilitated increasingly personalized IT-enabled healthcare delivery and practice (Glaser, Henley, Downing, Brinner, & Personalized Health Care Workgroup of the American Health Information Community, 2008) in much the same way as consumer products and services have become more personalized based on consumers' preferences and needs in commercial realms (Glaser et al., 2008). Therefore, we need to understand individuals' preferences and personality traits when studying whether patients will continue to use patient portals. Second, the literature has, to some extent, ignored health emotion and, thus, not considered an important factor that influences whether patients will continue to use patient portals. Based on the emotional dissonance theory, we explore and clarify how health emotion drives patients' intention to continue to use patient portals. Third, we argue that different individuals' intention to continue to use patient portals follows distinct mechanisms. Hence, we examine the moderating influence that health emotion has on the relationship between personality traits and intention to continue to use HIT. We need to understand the interaction effect between health emotion and personality traits to provide customized guidelines for increasing the extent to which patients use patient portals. Fourth, we contribute to the health human-computer interaction (HCI) domain by addressing Wilson and Djamasbi's (2015) call for more research on the interaction between users (e.g., patients and caregivers) and HIT along the three major dimensions users, technology, and the environment. We expand our knowledge about health HCI by empirically investigating a clinical, special-purpose information technology (IT) that focuses on the patient-user group. Overall, our research can help healthcare practitioners and HIT vendors understand why some individuals intend to continue to use patient portals and others do not.

2 Research Background

2.1 Health Human-computer Interaction and HIT Adoption and Use

Human-computer interaction (HCI) examines the relationships between humans (users) and computers (Benbasat, 2010; Booth, 1989). HCI research has traditionally focused on explaining why users adopt and continue to use contemporary technologies and how these systems can improve users' quality of life (Abowd & Mynatt, 2000). With increased demands for improved quality and lower costs associated with healthcare, health HCI research has become increasingly crucial for identifying gaps in continuous use of patient-centric medical devices and providing an innovative framework for resolving the current low use rates (Adarsha, Reader, & Erban, 2019; Wilson & Djamasbi, 2015). HCI research has a rich tradition of using various theories to understand people's technology-adoption behavior in both HIT and non-HIT contexts. Researchers have used many models and theories used to explore why users adopt and use patient portals and other online health systems, such as Davis' (1989) technology acceptance model (TAM) (Jung & Loria, 2010; Lazard et al., 2016; Lemire, Paré, Sicotte, & Harvey, 2008; Portz et al., 2019; Wilson & Lankton, 2004), Ajzen's (1991) theory of planned behavior (Emani et al., 2016), Petty and Cacioppo's (1986) elaboration likelihood model (Angst & Agarwal, 2009), Roger's (1995) diffusion of innovation theory (Carter, Corneille, Hall-Byers, Clark, & Younge, 2015), and Venkatesh, Morris, Gordon, and Davis' (2003) unified technology of acceptance and use of technology (UTAUT) model (Bozan, Parker, & Davey, 2016; Tavares & Oliveira, 2016). Chiasson, Kelley, and Downey (2015) used task-technology fit (Goodhue & Thompson, 1995) to study how diabetics use electronic health environments to understand treatments for their chronic condition. Still, they did not include personality traits or health emotion in their study. Kim and Park (2012) extended TAM by adding perceived threats to explore why users adopt various health information technologies. However, these studies either had mixed results or low variances (Bozan et al., 2016; Lazard et al., 2016). For example, Bozan et al. (2016) explored institutional factors including coercive, normative, and mimetic pressures and found that both coercive and mimetic pressures influenced elderly individuals' decision to adopt patient portals; however, their results only explained 28 percent of the low variance using R-squared (R^2), which suggests that additional factors exist beyond existing adoption theories and models to explain why individuals adopt health portals.

Although technology adoption studies may provide insights into the healthcare context, they do not clearly explain human-computer interaction in healthcare. HIT adoption behavior has a unique nature because individuals' motivation to use HIT may differ from their motivation to use non-HIT systems. While individuals

often engage in a simple cost-benefit analysis when deciding whether they will adopt particular technology (Luo, Warkentin, & Li, 2013), the decision-making process becomes more complicated if the technology is associated with or affects individuals' health. Few prior studies have examined health status (i.e., whether a person is healthy or ill) (Kulik & Mahler, 1987). For example, Xiao, Sharman, Rao, and Upadhyaya (2014) used health status (which they measured as health vs. ill health) to examine individuals' health and found that individuals who perceived their illness as severe interacted more in online chat rooms and conducted more diverse searches. Houston and Allison (2002) also found that patients with poor perceived health status tended to use the Internet and online chats more frequently to seek health-related information.

In their research, Brave and Nass (2009) implied that individuals have to cast aside emotions to interact with computers both efficiently and rationally and, thus, that emotion is at best marginally relevant to HCI and at worst oxymoronic. However, in exploring HCI, Bickmore and Picard (2005) determined the interaction between individuals and objects as they symbolically relate to themselves, others, or relationships. Prior research has determined that positive emotions such as happiness serve as the strongest motivators when individuals consider adopting Web technologies, which includes online communities and online support groups (Gruzd, 2013; Han et al., 2008). While many researchers have studied the impact that health status has on human-computer interaction and other decision-making purposes (se, e.g., Houston & Allison, 2002; Petrie, Weinman, Sharpe, & Buckley, 1996; Xiao et al., 2014), health emotion might better indicate how individuals interact with HIT.

2.2 Emotion and Health Emotion

Emotion refers to feelings about one's needs, goals, or concerns that stimuli evoke (Yuan & Dennis, 2016). While Gross and Muñoz (1995) noted that a true definition in the literature for emotion does not exist, Schachter and Singer (1962) defined emotion as "a state of physiological arousal and cognition appropriate to this state of arousal" (p. 380). The Merriam-Webster Dictionary defines emotion as "a conscious mental reaction (such as anger or fear) subjectively experienced as strong feeling usually directed toward a specific object and typically accompanied by physiological and behavioral changes in the body" ("Emotion", n.d.).

Rather than defining emotion, others such as Frijda (1994) have described emotion as a short-lived but intense effect on individuals' decision-making processes. To understand the distinction between emotion and attitude, one needs to understand the Tulving's (1983) nuance between semantic and episodic memory. Episodic memory stores information as experienced events, whereas semantic memory stores evolved information (i.e., knowledge and abstractions) that results from experience. We can find abstractions such as the evaluative continuum (i.e., attitude) in semantic memory and emotions in episodic memory (Tulving, 1983). Episodic (personal facts) and semantic memories (general facts) are mutually exclusive of each other, and no evidence exists that episodic memory (e.g., emotion) must be integrated with semantic memory (e.g., attitude) (Allen, Machleit, & Kleine, 1992; Breckler & Wiggins, 1989; Cohen, 1990). Druckman and McDermott (2008) suggested that individuals often act counter-intuitively by evoking emotion rather than just applying factual information. These feelings motivate individuals to take action by adding meaning and richness to all human experiences. Emotion can alter one's perceptions, physiology, and abilities (Tooby & Cosmides, 2000) and influence one's choices and behavior (Ariely & Loewenstein, 2006).

Bowman, Watson, and Trotman-Beasty (2006) developed the emotion and health scale to test the relationship between health and emotion by assessing ill patients' emotions. They distinguished health emotion from health status by indicating that emotion measures individuals' feelings about being unhealthy. Because individuals might consider health information more sensitive than non-health-related information, Anderson and Agarwal (2011) used 15 items from the Bowman et al. (2006) emotion and health scale to measure anger, disgust, fear, sadness, and joy related to an individual's current health status. Thus, prior research shows that health emotion plays a unique role when individuals must contend with choices that affect their health and life, similar to the feelings that individuals feel when making risk choices as Druckman and McDermott (2008) have described. Loewenstein (2005) also reported that emotions, such as hot-cold empathy gaps, have an important role in medical-related decision making. While others have not actually defined health emotion, for this research, we define health emotion as a conscious mental reaction (such as anger, fear, joy, etc.) to a strong feeling toward an individual's ongoing health conditions, which we refer to as health status.

Anderson and Agarwal (2011) determined that health emotion plays a role in whether individuals will allow their patient information to be released or accessed for reasons beyond patient care, such as marketing or research. Rahman (2015) suggested that an individual's health emotion could be an important factor to consider in adopting and using healthcare technologies. Health emotion is tied to individuals' emotional

feelings related to their ongoing health condition (Rahman, 2015). Because emotion plays an important role in influencing an individual's decision-making process, attitude, and actual behavior (Yuan & Dennis, 2016), we believe that we cannot completely understand individuals' intention to continue to use HIT without understanding the effect that health emotion has on the HIT decision-making process.

2.3 Individual Personality Traits

According to the American Psychology Association (2019), personality refers to three different characteristics: thinking, feeling, and behaving. McDougall (1932) first identified five distinguishable personality factors: intellect, character, temperament, disposition, and temper. Digman (1990) developed the five-factor model using the personality factors that researchers have proposed over the years. Researchers have explored the impact that personality traits have on how individuals use technology in other areas such as job performance (Barrick & Mount, 1991), online banking (Ko, Mancha, Beebe, & Yoon, 2012; Yoon & Steege, 2013), online commerce (Zhou & Lu,2011), and computer self-efficacy (Saleem et al., 2011). IS researchers believe that user differences such as cognitive styles and personality traits can affect how users use technology (Bariff & Lusk, 1977; McElroy et al., 2007) and that such differences could affect user satisfaction with a system and, therefore, system effectiveness eventually (Robey, 1983). In exploring online banking adoption, Ko et al. (2012) and Yoon and Steege (2013) used the five-factor model of personality to examine individuals' decision to use online banking. Ko et al. (2012) found that openness impacted Internet banking use but agreeableness did not. Yoon and Steege (2013) determined that openness influenced students' decision to use online banking. All personality traits significantly impact trust and, subsequently, the behavioral intention in the online commerce adoption environment (Zhou & Lu, 2011). Zhou and Lu (2011) also found that the personality traits except for conscientiousness and openness affect perceived usefulness.

In proposing their theory of reasoned action (TRA) Ajzen and Fishbein (1980) indirectly posited that personality would only impact behavior indirectly through constructs such as attitude. Specifically, Ajzen and Fishbein (1980) believed that extraversion and neuroticism would influence an individual's decision to behave such as using a technology. Devaraj, Easley, and Crant (2008a) determined that the big five personality constructs impacted usefulness and/or subjective norm in a modified technology acceptance model when individuals use collaborative technology. However, studies on HIT use rarely include dispositional factors, such as individuals' personality traits. In fact, the existing literature has largely ignored personality traits in profiling patient portal users. Tavares and Oliveira (2016) expressed concern since their model explained almost 26.8 percent of the variance in EHR portal technology use; however, individuals still adopted patient portals at an extremely low level and used it infrequently.

3 Research Model Development

Since healthcare technologies differ from other technologies, understanding why patients adopt and use healthcare technology remains an important and ongoing research topic not only for health and psychology researchers but also for IS researchers. Researchers examining technology adoption in other areas have included human psychology. We investigate patients' intention to continue to use patient portal technology from human personality psychology and health psychology perspectives. Informed by existing literature and emotional dissonance theory, we depict the research model and hypotheses we propose in Figure 1. In this study, we use intention to continue to use a patient portal as the dependent variable. In this section, we discuss these constructs and their importance when considering individuals' intention to continue to use healthcare technology.

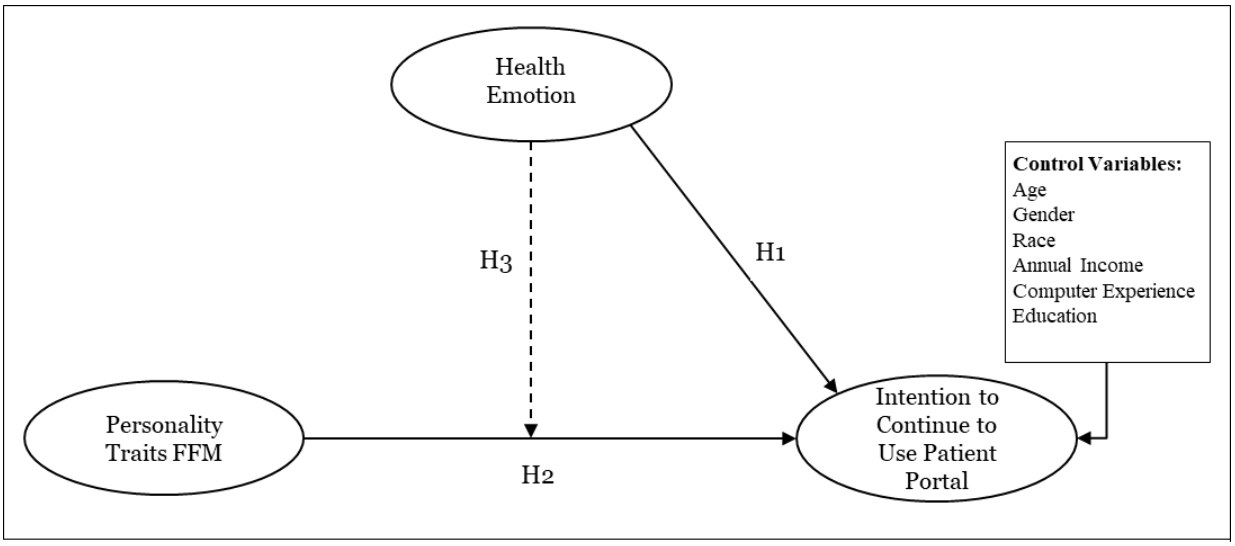

Figure 1. Research Model for Identifying the Role of Health Emotion and Personality Traits

3.1 Individual Health Emotion and Emotional Dissonance Theory

Emotions play an important role in human behavior, and individuals often use emotions in the decision-making process as a guide to form their judgment capabilities (Clore et al., 2001), which can influence their attitude and behavior. While attitude represents one's pre-dispositional view or an evaluative continuum of a behavior (Allen et al., 1992), emotion, represents feeling(s) about one's ongoing state or situation (Barrett, Mesquita, Ochsner, & Gross, 2007). Yuan and Dennis (2016) argued that individuals' emotions (positive or negative feelings) influence their attitude (e.g., perceive something as higher or lower value than otherwise). Factors related to events, situations, or environments can trigger emotions in individuals. When dealing with health, people often express a reaction to their illness using mood or emotion, which can influence their behavior. Health psychologists believe that emotion influences individuals' behavior and that each distinct emotion provokes distinct motivational goals that directly influence their behavior (Bowman et al., 2006). In other words, individuals' emotional state can influence and act as a catalyst to change their behavior. For example, an individual may have an unfavorable perception (i.e., attitude) toward taking medication; however, severe illness causes stronger emotions, which will influence their attitude toward taking medication to recover from the illness. Thus, we believe that health emotion plays an essential role in influencing people's inclination toward using healthcare technology.

Health emotion is a health psychology-based factor that represents how much concern an individual generally feels for their ongoing health situation (Leventhal, Meyer, & Nerenz, 1980). Bowman (2001) argued that most people would have an emotional response to their illness. The magnitude of the emotional response depends on an illness's severity such that a more severe illness will produce a stronger emotional response. Accordingly, the more health-related emotions individuals have, the more concern they will likely develop related to their health. Furthermore, they will likely do something to address the situation. Thus, the severity of individuals' illness affects their mood and health emotional state. In other words, an individual with a more severe sickness (an indication of poor health condition) will result in stronger health emotions. In contrast, most individuals with a less severe illness (a sign of better health condition) feel less health emotions concerning their health condition. Therefore, health emotion serves as an important indicator that implies how ill individuals perceive their immediate health status and plays an essential role in health-related decisions (Anderson & Agarwal, 2011).

Studies have suggested that emotions play a central role in the human motivational system and constitute a significant factor in determining individuals' sustaining behavior. Patients' health emotion influences their decision to adopt and use HIT, though few empirical studies have considered it thus far. In a rare study on health emotion, Anderson and Agarwal (2011) reported that individuals who experience poor health tend to have stronger health emotions. As emotions tend to produce some kind of behavioral homeostasis, individuals with strong health emotions will be more health conscious and place emphasis on improving their health, which may increase how frequently they use technology.

Emotional dissonance (Hochschild, 2012) is analogous with cognitive dissonance (Festinger, 1957). Thus, while cognitive dissonance refers to the inconsistency between an internal state and behavior, emotional dissonance refers to when individuals hold one or more contradictory emotions (i.e., emotional discrepancy). In this state, they will feel uncomfortable and experience dissonance. The cognitive dissonance theory that Festinger (1957) introduced posits that individuals have an inner drive to keep their cognition and behaviors in harmony and avoid conflicting cognitions or disharmony (i.e., dissonance) to maintain cognitive consistency. At its essence, the theory posits that dissonance or inconsistency between cognition and behavior produces a sense of mental discomfort that causes people to take action that change and eradicate the dissonance. For example, when people smoke (behavior) and know that smoking negatively impacts their health (cognition), they are cognitive dissonant. Both emotional and cognitive dissonance theories posit that experiencing dissonance leads to an uncomfortable state of tension that stimulates individuals to take action to reduce that tension (Pugh, Groth, & Hennig-Thurau, 2011). In our context here, we argue that, due to emotional dissonance theory, people will want to keep harmony between their current emotional state (poor health) and aspiring emotional state (good health), which will result in increasing their intention to use patient portal technology. In other words, when people experience stronger health emotions due to poor health (emotion), they will attempt to take action by continuously using a patient portal (behavior) to reduce the tension and keep their emotions and behavior in harmony. Because Lu and Zhang (2019) determined that patient portal use improves individuals' communication and compliance with their physician and, subsequently, their health (Lu & Zhang, 2019), we posit that patients' intention to continue to use patient portals will enhance the harmonious state between their behavior and emotion. Thus, stronger health emotions (an indication of poor health) will increase patients' intention to continue to use a patient portal. Thus, we hypothesize:

H1: Individuals with stronger health emotions intend to continue to use patient portals more than individuals with weaker health emotions.

3.2 Five-Factor Model of Personality

Research on personality traits has often used the five-factor model (FFM) (McCrae & John, 1992) to explain individual behavior. The literature on IT adoption has extensively studied personality traits (Devaraj, Easley, & Crant, 2008b; Korukonda, 2007; Korzaan & Boswell, 2008; McElroy et al. 2007; Thatcher & Perrewe, 2002) and found that factors such as individuals' reactions to technology and personality often play an integral role. IS researchers believe that individual cognitive differences relate to system success because individual differences affect user satisfaction with a system and, ultimately, its effectiveness (Robey & Markus, 1984; Zmud, 1979). In this study, we investigate the role of personality traits using FFM, which comprises five personality traits (i.e., conscientiousness, extraversion, neuroticism, openness to experience, and agreeableness, in the healthcare portal context.

Conscientiousness refers to conformity or dependability and connects to an individual's degree of self-control. Highly conscientious individuals often have more motivation to achieve and improve their situation. In contrast, individuals low in conscientiousness lack dependability and have low motivation, poor self-control, and a cynical outlook. Conscientious individuals have high self-efficacy (Judge, Jackson, Shaw, Scott, & Rich, 2007; Saleem et al., 2011) and tend to enjoy technology (Hunsinger, Poirier, & Feldman, 2008), especially if they perceive it as beneficial (Devaraj et al., 2008a). Individuals with higher conscientiousness are more likely to have a positive experience with technology and more likely to enjoy using technology in their daily life. We predict that we can extend this finding into the healthcare context such that conscientious people will try to improve their health situation by exploiting available technologies. Thus, we hypothesize:

H2a: Individuals high in conscientiousness intend to continue to use patient portals more than individuals low in conscientiousness.

Extraversion refers to the extent to which individuals engage with their environment. Individuals high in extraversion are social, active, and outgoing and place a high value on close and warm interpersonal relationships (Watson & Clark, 1997). On the other hand, an individual low in extraversion (which researchers refer to as introverted individuals) are unsocial and self-centered and lack interpersonal relationships. Extraverted individuals tend to have positive attitudes toward technology use (Hunsinger et al., 2008) and an inclination to engage more with technology, such as communicating with others via social networks (Kock & Moqbel, 2019; Kock, Moqbel, Barton, & Bartelt, 2016; Moore & McElroy, 2012; Moqbel & Iftab, 2015; Moqbel & Nah, 2017; Moqbel, Nevo, & Kock, 2013) and mobile phones (Bianchi & Phillips,

2005). Thus, we argue that extraverted individuals are more likely to continue to use technology for their healthcare needs as such technology helps them to communicate information. Thus, we hypothesize:

H2b: Individuals high in extraversion intend to continue to use patient portals more than individuals low in extraversion.

Insecurity, anxiousness, and hostility characterize neuroticism (or emotional instability) (Devaraj et al., 2008b). Individuals high in neuroticism generally exhibit anxious, nervous, and tense behavior (Korzaan & Boswell, 2008; Osatuyi, 2015). In contrast, individuals low in neuroticism exhibit more stable and confident behavior (Devaraj et al. 2008a). In the technology-adoption context, researchers have linked neuroticism to computer anxiety (Korukonda, 2007; Korzaan & Boswell, 2008), a lack of social skills, and the avoidance of situations that require taking control (Judge, Locke, & Durham, 1997). Technology threatens highly neurotic individuals, and they avoid it to reduce anxiety. For example, Amiel and Sargent (2004) found that low neuroticism was associated with greater use of text-messaging tools. Thus, we hypothesize:

H2c: Individuals low in neuroticism intend to continue to use patient portals more than individuals high in neuroticism.

Individuals who exhibit openness also demonstrate stronger curiosity, directness, and willingness to accept or explore new experiences without reservations. Individuals high in openness are more accepting and less judgmental. They tolerate change and readily embrace new ideas (Korzaan & Boswell, 2008). Conversely, individuals low in openness tend to lack curiosity and exhibit resistance toward new experiences. Researchers have found openness to influence the extent to which individuals use technology such as the Internet (McElroy et al., 2007), social media (Correa, Hinsley, & De Zuniga, 2010), alternate communication methods (Ross et al., 2009), and new technology (Devaraj et al., 2008a). Based on the literature, we believe individuals high in openness will more likely adopt and use healthcare technology, such as a patient portal system. Thus, we hypothesize:

H2d: Individuals high in openness to new experiences intend to continue to use patient portals more than individuals low in openness.

Agreeableness describes individuals' interpersonal capability to accommodate, sympathize with, and trust others. While highly agreeable people tend to be flexible and willing to change, individuals low in agreeableness can be difficult to work with and tend to resist changing situations. Agreeable individuals are social and have many friends. Studies suggest that agreeable individuals will be more persistent in using challenging-to-access technology (Wyatt & Phillips, 2005). Thus, highly agreeable individuals' more forgiving and tolerant nature may allow them to use systems even when technological issues frustrate and challenge them, such as when one must remember a password or request a password reset (Landers & Lounsbury, 2006). Thus, we hypothesize:

H2e: Individuals high in agreeableness intend to continue to use patient portals more than individuals low in agreeableness.

Researchers have established that individuals' emotions related to their health play an essential role in how they deal with various health-related decisions (Anderson & Agarwal, 2011). Individuals tend to focus on improving their health using any means when ill. As poor health conditions lead to stronger health emotions, we predict that stronger health emotions will modify the relationships between individuals' personality traits and their intention to continue to use healthcare technologies in efforts to improve their health condition except for individuals with a strong inclination toward neuroticism. We expect that stronger health emotions will moderate the relationship between neuroticism and intention to continue to use such that stronger health emotions will weaken the negative relationship. Thus, we hypothesize:

H3a: Health emotion moderates the relationship between conscientiousness and intention to continue to use such that strong health emotions strengthen the relationship.

H3b: Health emotion moderates the relationship between extraversion and intention to continue to use such that strong health emotions strengthen the relationship.

H3c: Health emotion moderates the relationship between neuroticism and intention to continue to use such that strong health emotions weaken the relationship.

H3d: Health emotion moderates the relationship between openness to experience and intention to continue to use such that strong health emotions strengthen the relationship.

H3e: Health emotion moderates the relationship between agreeableness and intention to continue to use such that strong health emotions strengthen the relationship.

4 Research Method

4.1 Data-collection Procedure

We recruited study participants from a research participant registry at a major medical center in the United States' Midwest. After receiving institutional review board approval, we invited participants through emails to complete an online survey. We provided no monetary compensation. Since we explored continuous use post adoption, we screened participants to ensure we only included individuals who consented to participate, were over 18 years old, and indicated that they had prior experience using patient portals. The online survey took approximately 10 to 15 minutes to complete. Respondents participated in the survey voluntarily, and we assured them that we de-identified the data and would only use it for research purposes in an aggregated format. In total, 187 patients completed the online survey.

4.2 Measurements

We used established measurement items from extant studies to develop the survey instrument. We adapted items for personality traits from prior studies (Gu & Wang, 2009; Junglas, Johnson, & Spitzmüller, 2008; Korzaan & Boswell, 2008). To measure health emotions, we derived items from Anderson & Agarwal (2011) and Bowman et al. (2006). We used measures from Lowry, Gaskin, and Moody (2015) and Kock et al. (2016) to measure individuals' intention to continue to use patient portals. We present the survey items in Appendix A. We used a five-point Likert scale for all measurement items (1 = strongly disagree, 5 = strongly agree). We also used several control variables (age, race, gender, income, marital status, education, and prior computer experience) to rule out any alternative ways to explain our results. Past studies have reported that gender, age, and education play a role in technology use (Dinev & Hart, 2004; Herath & Rao, 2009; Johnston & Warkentin, 2010). Other studies have found income (Dinev & Hart, 2004; Kim, Ferrin, & Rao, 2008; Pires, Stanton, & Eckford, 2004) and prior experience with technology (Johnston & Warkentin, 2010; Kim et al., 2008) as important control variables for research on technology use.

5 Results

5.1 Data Analysis

We analyzed our research model using a second-generation causal path-modeling technique, partial least squares structural equation modeling (PLS-SEM) (Chin, Marcolin, & Newsted, 2003; Haenlein & Kaplan, 2004). This approach allows researchers to examine the structural equation model (SEM) for path analysis and measurement models simultaneously (Gefen, Straub, & Boudreau, 2000). Compared to conventional analysis methods (e.g., regression analysis) that disregard the interrelationships between latent constructs that multi-item measurement instruments measure (Chin, 1998), SEM is a statistical methodology that takes a confirmatory (i.e., hypothesis-testing) approach to evaluating causal relationships among latent constructs (i.e., a structural theory) (Byrne, 2001). PLS suits exploratory models, small sample sizes, and non-normal distributions (Chin, 1998; Gefen & Straub, 2005).

We used WarpPLS 6.0 to assess the psychometric properties (internal consistency reliability, convergent validity, and discriminant validity) of the measurement items and the SEM analysis. In particular, we used WarpPLS (Kock, 2019) due to some of its advanced features that we needed in our study, such as outputs that enable multivariate normality and tests for multicollinearity, common method bias, and predictive validity. We summarize the results for the measurement model in Tables 1 and 2. The results indicate that our measurement instrument had acceptable reliability because composite reliability values exceeded the recommended threshold of .70 (see Table 1) (Fornell & Larcker, 1981).

Discriminant validity was acceptable since the square roots of the average variance extracted (AVE) exceeded the correlations among latent variables (see Table 2) (Fornell & Larcker, 1981). The factor loadings for all items were greater than the minimum recommended threshold of 0.50, which indicates that our measurement instrument had acceptable convergent validity. The variance inflation factor (VIF) values for all the items were lower than 3.3, which suggests that multicollinearity did not pose an issue for this

measurement instrument. We also assessed multivariate normal distribution (normal) and found that some variables did not follow a normal distribution, which justified our choice to use PLS-based SEM in this study.

Table 1. Measurement Model Summary

Construct	Item	Loading	Composite reliability	VIF	Normal
Health emotion (HE)	HE1	(0.876)	0.878	1.727	Yes
	HE5R	(0.893)			
Neuroticism (NEU)	NEU1	(0.872)	0.865	1.578	Yes
	NEU2	(0.864)			
	NEU3	(0.736)			
Agreeableness (AGR)	AGR1	(0.619)	0.786	2.236	Yes
	AGR2	(0.731)			
	AGR3	(0.668)			
	AGR4	(0.745)			
Conscientiousness (CON)	CON1	(0.723)	0.842	1.971	Yes
	CON2	(0.737)			
	CON3	(0.789)			
	CON4	(0.773)			
Extraversion (EXT)	EXT1	(0.902)	0.884	1.645	Yes
	EXT2	(0.918)			
	EXT3	(0.787)			
	EXTR4	(0.608)			
Openness to experience (OTE)	OTE1	(0.749)	0.794	2.093	Yes
	OTE2	(0.741)			
	OTE3	(0.712)			
	OTE4R	(0.595)			
Intended continuous use (ICU)	ICU1	(0.836)	0.831	1.676	No
	ICU2	(0.849)			

Note: all loadings were significant at $p < 0.001$.
CR = composite reliability, FVIF = full collinearity variance information factor, normal = normal (robust Jarque–Bera), HE = health emotion, NEU = neuroticism, AGR = agreeableness, CON = conscientiousness, EXT = extraversion, OTE = openness to experience, ICU = intention to continue to use.

Table 2. Discriminant Validity Analysis

	HE	EXT	NEU	AGR	CON	OTE	IU
HE	**(0.885)**						
EXT	-0.133	**(0.813)**					
NEU	0.374	-0.164	**(0.826)**				
AGR	-0.168	0.377	-0.032	**(0.693)**			
CON	-0.199	0.081	-0.094	0.585	**(0.756)**		
OTE	-0.135	0.310	-0.144	0.427	0.435	**(0.702)**	
ICU	0.279	0.372	-0.035	0.251	0.123	0.275	**(0.843)**

Note: we show square roots of average variances extracted (AVE) on the diagonal in bold.
HE = health emotion, NEU = neuroticism, AGR = agreeableness, CON = conscientiousness, EXT = extraversion, OTE = openness to experience, ICU = intention to continue to use.

5.2 Descriptive Statistics

Of the 187 respondents, 84 percent were white, 45.1 percent were married, 75.3 percent were female, and 37.6 percent had a bachelor's degree. According to U.S. demographic statistics for 2019 from the U.S. Census Bureau, 76.5 percent of the U.S. population are white, 48 percent are married, 50.8 percent are female, and 31.5 percent have a bachelor's degree. Although our sample contained relatively more female respondents compared to the U.S. population, we believe that our participant sample represents the U.S. population well when we consider the other demographic characteristics. For example, our participants' race, marital status, and educational background all align with the U.S. population's demographic statistics. As we used a different scale for age compared to U.S. Census Bureau, we could not compare data based on age. We show the complete demographics in Table 3.

Table 3. Demographics

	Demographic group	N	Percent (%)
Gender	Female	141	75.3%
	Male	46	24.7%
Age	18-29	69	36.9%
	30 to 39	35	18.7%
	40 to 49	30	16.0%
	50 to 59	24	12.8%
	Over 60	29	15.51
Marital status	Married	85	45.1%
	Single	82	44.1%
	Divorced or widowed	20	10.8%
Ethnicity	White	157	84.0%
	Asian Pacific Islander	7	3.7%
	Hispanic	10	3.7%
	Black	6	3.2%
Education	High school diplomas	2	1.1%
	Some college	51	27.4%
	Bachelor's degree	63	37.6%
	Masters, postgraduate, doctorates, or professional degrees	71	37.6%

5.3 Hypothesis Analysis

Table 4 shows the stepwise SEM analysis results, which includes the standardized path coefficients, the significance of the paths coefficients, and the variance (R^2) that the exogenous variables explained. We first assessed the effect that the control variables and health emotion on intended continuous use (Model 1). Health emotion had a significant effect on intention to continue to use and explained 13 percent of the variance. The control variables were not significant. In the second step (Model 2), we added personality trait constructs to the previous model. We found that health emotion and all personality traits constructs, except for neuroticism and agreeableness, were significant and explained 35 percent of the variance in intention to continue to use.

Finally, we used a final model (Model 3) to test the control variables, main effects, and moderating effects, which explained 40 percent of the variance in intention to continue to use. Health emotion and all personality traits, except for neuroticism, had a significant effect on intention to continue to use. We found significant results for two of our moderation hypotheses (i.e., H3a to H3e): health emotion significantly moderated the relationship between conscientiousness and intention to continue to use patient portals (H3a) ($\beta = 0.12$, $p < 0.05$) and the relationship between neuroticism and intention to continue to use patient portals (H3c) ($\beta = 0.16$, $p < 0.01$).

Table 4. Path Coefficients of Stewise Structural Model Analysis

		Model 1	Model 2	Model 3
		Intention to continue to use	Intention to continue to use	Intention to continue to use
Control VARIABLES	Age	.06 n.s.	.05 n.s.	.07 n.s.
	Gender (female)	-.06 n.s.	-.03 n.s.	-.04 n.s.
	Education	-.09 n.s.	-.011 n.s.	-.011 n.s.
	Race (white)	.11 n.s.	.10 n.s.	.10 n.s.
	Computer experience	-.07 n.s.	-.09 n.s.	-.09 n.s.
	Income	.01 n.s.	-.04 n.s.	-.04 n.s.
Main effects	Health emotion (HE)	.30***	.33***	.30***
	NEU		-.09 n.s.	-0.09 n.s.
	AGR		.09 n.s.	0.12*
	CON		.13*	0.12*
	EXT		.26***	0.25***
	OTE		.19**	0.13*
Interaction effects	NEU x HE → IU			0.16*
	AGR x HE → IU			-0.07 n.s.
	CON x HE → IU			0.12*
	EXT x HE → IU			0.01 n.s.
	OTE x HE → IU			-0.01 n.s.
	R2	.13	.35	.40

Note: *p < 0.05, **p < 0.01, ***p < 0.001, n.s.: not significant
HE = health emotion, NEU = neuroticism, AGR = agreeableness, CON = conscientiousness, EXT = extraversion, OTE = openness to experience, ICU = intention to continue to use.

When comparing the R^2 values for Model 2 to Model 1, the explained variance in intention to continue to use increased by 22 percentage points (from 13% to 35%). When comparing the R^2 values for Model 2 to Model 3, the explained variance in intention to continue to use increased from 35 percent to 40 percent. In other words, personality traits improved the variance in intention to continue to use the model by 22 percent. The moderation effects of health emotion increased that value further by five percent to 40 percent.

6 Discussion

Researchers have extensively explored the impact that personality traits have on how individuals use technology in other areas such as collaborative technology (Devaraj et al., 2008a, 2008b); computer anxiety, privacy concerns, and computer self-efficacy (Korukonda, 2007; Korzaan & Boswell, 2008; Saleem et al., 2011; Thatcher & Perrewe, 2002); Internet use (McElroy et al., 2007); and online banking adoption (Ko et al., 2012; Yoon & Steege, 2013). Although these studies have helped explain the factors that influence non-HIT adoption, we do not sufficiently understand the influence that patient characteristics such as personality traits have on their intention to continue to use HIT. Similarly, the literature has clearly established emotion's importance in the decision-making process. For example, Druckman and McDermott (2008) reported that emotion had a significance influence on whether individuals make risky choices and called for integrating emotions into different research areas. Gruzd (2013) reported that emotion is one of the strongest motivators for why individuals use Web technologies (i.e., online communities). Yuan and Dennis (2016) have also reported the significance of emotion in technology-adoption decisions, such as in online auctions. In some empirical studies, scholars studied patient health status (Xiao et al., 2014) and health emotion (Anderson & Agarwal, 2011) in the broad HIT-adoption context; however, researchers have not yet studied whether these factors influence individuals' intention to continue to use HIT. Our study complements the existing HIT

literature by presenting a holistic model of patient-specific predictors, which includes health emotion, personality traits, and their interaction terms, which combined explained 40 percent of individuals' intention to continue to use HIT.

With this study, we make several important research contributions. First, via the lens of emotional dissonance theory, we found that health emotion had a positive effect on individuals' intention to continue to use patient portals (RQ1), which implies that individuals who experience strong health emotions (otherwise translated as poor health) will be more likely to use patient portals in an effort to improve their health. For individuals with health issues, their health emotion superseded all other factors when they made healthcare technology-usage decisions. This study extends our limited knowledge on the role of health emotion. Emotions greatly affect human decision making in various contexts (Druckman & McDermott, 2008), and researchers have studied patients' emotions related to their health in the healthcare context (e.g., Bowman et al., 2006; Trumbo, McComas, & Kannaovakun, 2007) but rarely in the HIT context. Anderson and Agarwal (2011) have argued that HIT represents a unique context because it involves "the emotion linked to one's medical state". A rare empirical study on health emotion and technology adoption, Anderson and Agarwal found that health emotion significantly impacts patients' willingness to disclose health information. Our empirical research contributes to the health emotion literature by adding insights into the role that health emotion plays in patients' intention to continue to use patient portals.

Second, our results provide substantial evidence that support the assertion that individuals' personality traits explain the variation in their intention to continue to use patient portals (RQ2). In response to calls for research to examine the role of personality traits and their influence on IT situation-specific individual differences (Saleem et al., 2011; Thatcher & Perrewe, 2002), we investigate individuals' dispositional factors in the continuous technology-usage context and expand the existing research on personality traits and their impacts on technology-use behaviors. Our results show that personality traits increased the variance in intention to continue to use by 22 percent beyond the variance that health emotions alone explained. Four of the five personality traits we studied (i.e., agreeableness, conscientious, openness to experience, and extroversion) had a significant role in individuals' decision to continue to use patient portals. One finding indicates that individuals high in extroversion are more likely to take advantage of the patient portal technology due to their assertive personality. Highly conscientious individuals are more likely to use the patient portal technology due to their careful, organized, responsible, and achievement-oriented personality (Gu & Wang, 2009; Junglas et al., 2008; Korzaan & Boswell, 2008). Individuals with these traits are more likely to use patient portals to attend to their own health responsibly. Open-mindedness characterizes individuals high in openness to experiences (Korzaan & Boswell, 2008). Therefore, individuals high in openness were more likely to continue to use patient portals in the future. These results concur with Ko et al. (2012) and Yoon and Steege (2013) who also found that openness influenced the likelihood that an individual would use online banking. More agreeable patients who typically have a forgiving and tolerant nature (Landers & Lounsbury, 2006) tend to use and continue to use patient portals. These results directly contradict Ko et al.'s (2012) findings that agreeableness does not influence an individual's decision to use online banking. However, our results did not support the direct impact of neuroticism. Indeed, we found that neuroticism had a negative and significant influence only when individuals had weak health emotions (see Figure 2). Perhaps, these results are compounded because some individuals experience strong health emotions for non-catastrophic or non-life-threatening health conditions due to their mental instability. Our findings suggest that the well-documented body of literature on personality traits also has a significant ramification on HIT-use behavior.

Third, we assessed whether the big five personality traits moderated the effect that health emotions had on intention to continue to use patient portals (RQ3). We found that neuroticism strongly reduced individuals' intention to continue to use patient portals when they had weak health emotions. In other words, weak health emotions positively moderated (or weakened) the negative relationship between neuroticism and intention to continue to use patient portals. As for why, individuals with weak health emotions are usually healthier and, thus, may believe that they do not need to use portal portals to monitor their health. In contrast, when users experienced strong health emotions, the negative effect that neuroticism had on intention to continue to use patient portals diminished. In other words, individuals in good health (who experienced weak health emotions) and who were stable, confident, in control, and well adjusted (low neuroticism) (Devaraj et al., 2008a) preferred to use patient portals more than individuals higher in neuroticism. We also found that health emotions positively moderated (or strengthened) the positive relationship between conscientiousness and intention to continue to use patient portals. In other words, for individuals with strong health emotions (poor health), conscientiousness strongly increased their intention to continue to use patient portals (see

Figure 3). Thus, we augment the post-technology-adoption literature by examining the interplay between patients' personality characteristics and their health emotions.

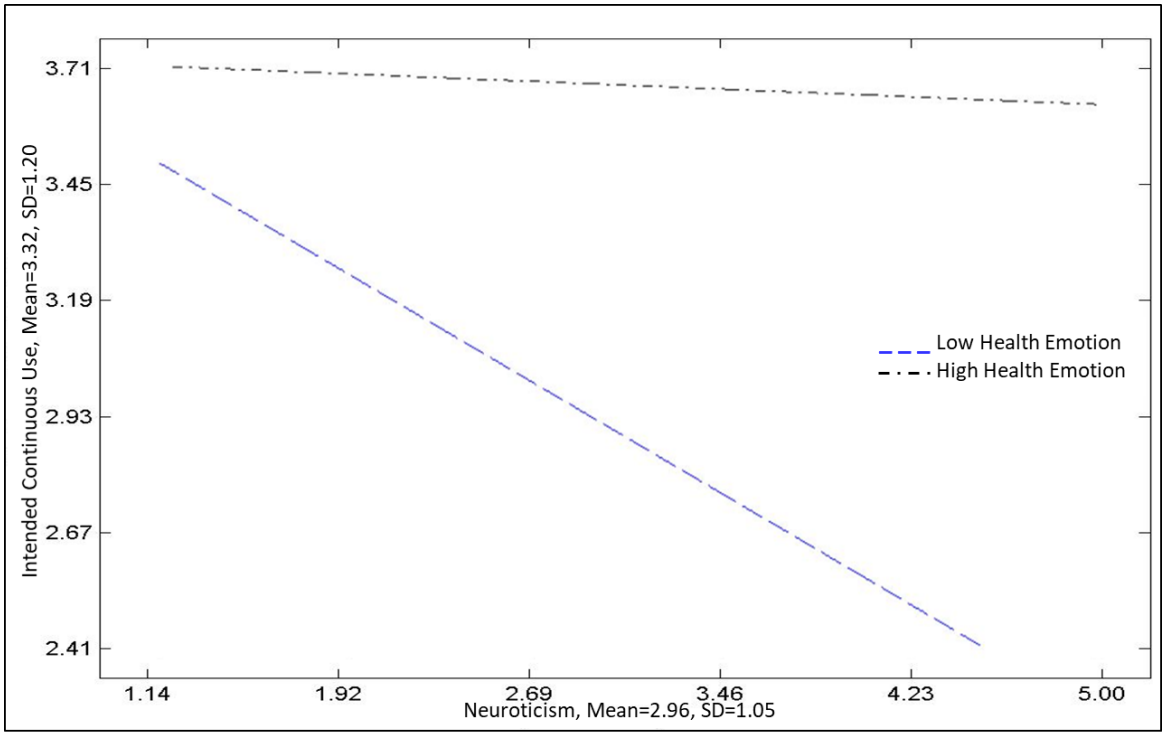

Figure 2. Moderation of Health Emotion on the Relationship between Neuroticism and Intention to Continue to Use Patient Portals

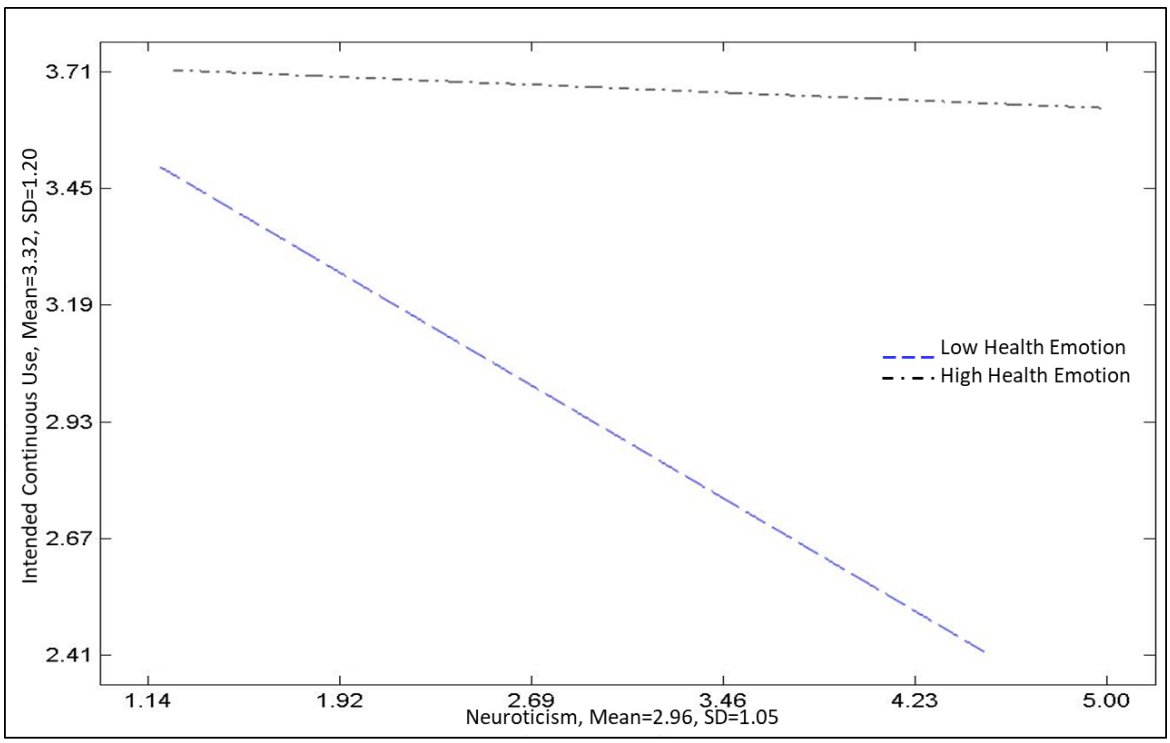

Figure 3. Moderation of Health Emotion on the Relationship between Conscientiousness and Intention to Continue to Use Patient Portals

Wilson and Djamasbi (2015) explained that we need to consider the interaction between users (e.g., patients and caregivers) and HIT, especially in a health HCI domain. They argue that health HCI research covers three major axes: users, technology, and the environment. One can categorize users as healthcare professionals or patients/caregivers. Technology attributes that can be categorized into either general-purpose IT and specialized health IT include technology type, physical attributes (e.g., size, shape, etc.), access/interaction type, and functionality. The environment refers to conditions under which individuals use technology, and one can categorize it as clinical or non-clinical. One can use the framework to contextualize health HCI studies. Accordingly, we can categorize our study as analyzing the patient/caregiver user group and special-purpose health IT (i.e., patient portal) in a clinical context.

Fourth, with this study, we contribute to the health HCI literature by expanding our knowledge of user characteristics and providing insights into the role that health emotion, personality traits, and the interaction between them play in individuals' intention to continue to use patient portals. We contribute to the literature by addressing Wilson and Djamasbi's (2015) call for more research on health HCI.

This study has practical implications as well. Our findings can help practitioners who implement patient portal systems to increase patient enrollment and target this technology to patients according to their traits to encourage continued engagement. Our findings suggest that patient portal vendors need to develop applications that personalize healthcare delivery and practice based on patients' needs and preferences. Vendors can provide users with a system tailored to their personality and their health needs given the fast-paced advances in AI and big data analytics technologies. Better understanding the effect that personality has on HIT continuous use will allow healthcare organizations and HIT vendors to target their systems and services to specific patients. Therefore, vendors and organizations that understand how their patients' personalities and health emotions impact how they use these systems may have a competitive advantage over others who do not.

7 Limitations and Future Research

Like all empirical investigations, this study has some limitations. First, since we adopted a cross-sectional study design, we cannot establish a definitive causal relationship between the exogenous and dependent variables. Thus, future research may analyze longitudinal data to support causal relationships. Second, we used perception-based and self-reported data. Future efforts should explore more objective-based data such as patient's login frequencies, use time, and so on. Researchers may also want to control for the severity of patients' illnesses in future studies. In the US, the Health Insurance Portability and Accountability Act of 1996 (HIPAA) requires that patients have access to their health records. Merely providing access to health records through a portal does not truly address this directive if patients do not continue to use it. Thus, researchers need to investigate what factors influence and encourage patients to continue to use healthcare technologies, which include patient portals. Better understanding patient portal user characteristics may lead to future research on patient portals that uses a more design- or user experience-based approach, which could enable better design, technology experience, and increased adoption. It also would be interesting to see future studies that explore using artificial intelligence (AI) (Eglash et al., 2019; Robert et al., 2020a; Robert, Pierce, Marquis, Kim, & Alahmad, 2020b) to capture patients' personality traits using a design science approach, which would enable vendors to customize their systems according to patients' personalities. Researchers have suggested that privacy and trust connect closely to HIT-use behaviors. Campbell (2019) determined that individuals were more likely to share personal information in a business-to-consumer environment if trust existed in the relationship. Future research should perhaps explore how trust impacts whether individuals continue to use patient portals as Campbell (2019) has noted.

8 Conclusion

We need to understand individual differences in technology adoption and continuous use as these differences affect individuals' behavior towards technology (Anderson & Agarwal, 2011; Bariff & Lusk, 1977; McElroy et al., 2007; Robey, 1983). We also need to understand individual differences for patient portal continuous use as well. We found that user personality traits captured using FFM and user health emotion and their interaction play an important role in individuals' intention to continue to use patient portals through the lens of emotional dissonance theory. Our findings provide healthcare organizations with an integrated view of patient portal use behavior and indicate that they may use knowledge about users' characteristics or health emotion to increase patient enrolment and engagement by better targeting their services and products to specific patient populations.

References

Abowd, G. D., & Mynatt, E. D. (2000). Charting past, present, and future research in ubiquitous computing. *ACM Transactions on Computer-Human Interaction, 7*(1), 29-58.

Adarsha, A. S., Reader, K., & Erban, S. (2019). User experience, IoMT, and healthcare. *AIS Transactions on Human-Computer Interaction*, *11*(4), 264-273.

Ajzen, I. (1991). The theory of planned behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211.

Ajzen, I., & Fishbein, M. (1980). *Understanding attitudes and predicting social behavior*. Englewood Cliffs, NJ: Prentice-Hall.

Allen, C. T., Machleit, K. A., & Kleine, S. S. (1992). A comparison of attitudes and emotions as predictors of behavior at diverse levels of behavioral experience. *Journal of Consumer Research*, *18*(4), 493-504.

American Psychology Association. (2019). *Personality*. Retrieved from https://www.apa.org/topics/personality/

Amiel, T., & Sargent, S. L. (2004). Individual differences in Internet usage motives. *Computers in Human Behavior*, *20*(6), 711-726.

Ancker, J. S., Barrón, Y., Rockoff, M. L., Hauser, D., Pichardo, M., Szerencsy, A., & Calman, N. (2011). Use of an electronic patient portal among disadvantaged populations. *Journal of General Internal Medicine*, *26*(10), 1117-1123.

Anderson, C. L., & Agarwal, R. (2011). The digitization of healthcare: Boundary risks, emotion, and consumer willingness to disclose personal health information. *Information Systems Research*, *22*(3), 469-490.

Angst, C. M., & Agarwal, R. (2009). Adoption of electronic health records in the presence of privacy concerns: The elaboration likelihood model and individual persuasion. *MIS Quarterly*, *33*(2), 339-370.

Ariely, D., & Loewenstein, G. (2006). The heat of the moment: The effect of sexual arousal on sexual decision making. *Journal of Behavioral Decision Making*, *19*(2), 87-98.

Bariff, M. L., & Lusk, E. J. (1977). Cognitive and personality tests for the design of management information systems. *Management Science*, *23*(8), 820-829.

Barrett, L. F., Mesquita, B., Ochsner, K. N., & Gross, J. J. (2007). The experience of emotion. *Annual Review of Psychology*, *58*, 373-403.

Barrick, M. R., & Mount, M. K. (1991). The big five personality dimensions and job performance: a meta-analysis. *Personnel Psychology*, *44*(1), 1-26.

Benbasat, I. (2010). HCI research: Future challenges and directions. *AIS Transactions on Human-Computer Interaction*, *2*(2), 16-21.

Bianchi, A., & Phillips, J. G. (2005). Psychological predictors of problem mobile phone use. *CyberPsychology & Behavior*, *8*(1), 39-51.

Bickmore, T. W., & Picard, R. W. (2005). Establishing and maintaining long-term human-computer relationships. *ACM Transactions on Computer-Human Interaction, 12*(2), 293-327.

Board of Governors of the Federal Reserve System. (2016*). Consumers and mobile financial services 2016.* Retrieved from https://www.federalreserve.gov/econresdata/consumers-and-mobile-financial-services-report-201603.pdf

Booth, P. A. (1989). *An introduction to human-computer interaction*. London, UK: Lawrence Erlbaum Associates.

Bowman, G. S. (2001). Emotions and illness. *Journal of Advanced Nursing*, *34*(2), 256-263.

Bowman, G., Watson, R., & Trotman-Beasty, A. (2006). Primary emotions in patients after myocardial infarction. *Journal of Advanced Nursing*, *53*(6), 636-645.

Bozan, K., Parker, K., & Davey, B. (2016). A closer look at the social influence construct in the UTAUT model: An institutional theory based approach to investigate health IT adoption patterns of the elderly. In Proceedings of the *49th Hawaii International Conference on System Sciences*.

Brave, S., & Nass, C. (2009). Emotion in human-computer interaction. In A. Sears & J. A. Jacko (Eds.), *The human-computer interaction handbook: Fundamentals, evolving technologies and emerging applications* (pp. 81-96). Boca Raten, FL: Taylor & Francis Group.

Breckler, S. J., & Wiggins, E. C. (1989). Affect versus evaluation in the structure of attitudes. *Journal of Experimental Social Psychology*, *25*(3), 253-271.

Byrne, B. M. (2001). Structural equation modeling with AMOS, EQS, and LISREL: Comparative approaches to testing for the factorial validity of a measuring instrument. *International Journal of Testing*, *1*(1), 55-86.

Campbell, D. E. (2019). A relational build-up model of consumer intention to self-disclose personal information in e-commerce B2C relationships. *AIS Transactions on Human-Computer Interaction*, *11*(1), 33-53.

Carter, L., Corneille, M., Hall-Byers, N. M., Clark, T., & Younge, S. N. (2015). Exploring user acceptance of a text-message base health intervention among young African Americans. *AIS Transactions on Human-Computer Interaction*, *7*(3), 110-124.

Chiasson, M., Kelley, H., & Downey, A. (2015). Understanding task-performance chain feed-forward and feedback relationships in e-health. *AIS Transactions on Human-Computer Interaction*, *7*(3), 167-190.

Chin, W. W. (1998). Commentary: Issues and opinion on structural equation modeling. *MIS Quarterly*, *22*(1), vii-xvi.

Chin, W. W., Marcolin, B. L., & Newsted, P. R. (2003). A partial least squares latent variable modeling approach for measuring interaction effects: Results from a Monte Carlo simulation study and an electronic-mail emotion/adoption study. *Information Systems Research*, *14*(2), 189-217.

Clement, J. (2019). Number of digital buyers worldwide from 2014 to 2021 (in billions). *Statista.* Retrieved from https://www.statista.com/statistics/251666/number-of-digital-buyers-worldwide/

Clore, G. L., Gasper, K., & Garvin, E. (2001). Affect as information. In J. P. Forgas, (Ed.), *Handbook of affect and social cognition*. Mahwah, NJ: Lawrence Erlbaum Associates Publishers.

Cohen, J. B. (1990). Attitude, affect, and consumer behavior. In B. Moore & A. Isen (Eds.), *Affect and social behavior* (pp. 152-206). Cambridge, UK: Cambridge University Press.

Correa, T., Hinsley, A. W., & De Zuniga, H. G. (2010). Who interacts on the Web? The intersection of users' personality and social media use. *Computers in Human Behavior*, *26*(2), 247-253.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319-340.

DeLone, W. H., & McLean, E. R. (1992). Information systems success: The quest for the dependent variable. *Information Systems Research*, *3*(1), 60-95.

Delone, W. H., & McLean, E. R. (2003). The DeLone and McLean model of information systems success: A ten-year update. *Journal of Management Information Systems*, *19*(4), 9-30.

Devaraj, S., & Kohli, R. (2000). Information technology payoff in the health-care industry: A longitudinal study. *Journal of Management Information Systems*, *16*(4), 41-67.

Devaraj, S., Easley, R. F., & Crant, J. M. (2008a). How does personality matter? Relating the five-factor model to technology acceptance and use. *Information Systems Research*, *19*(1), 93-105.

Devaraj, S., Easley, R. F., & Crant, J. M. (2008b). Research note-how does personality matter? Relating the five-factor model to technology acceptance and use. *Information Systems Research*, *19*(1), 93-105.

Digman, J. M. (1990). Personality structure: Emergence of the five-factor model. *Annual Review of Psychology*, *41*(1), 417-440.

Dinev, T., & Hart, P. (2004). Internet privacy concerns and their antecedents-measurement validity and a regression model. *Behaviour & Information Technology*, *23*(6), 413-422.

Druckman, J. N., & McDermott, R. (2008). Emotion and the framing of risky choice. *Political Behavior*, *30*(3), 297-321.

Eglash, R., Robert, L., Bennett, A., Robinson, K. P., Lachney, M., & Babbitt, W. (2019). Automation for the artisanal economy: Enhancing the economic and environmental sustainability of crafting professions with human-machine collaboration. *AI & Society*, *35*, 595-609.

Emani, S., Healey, M., Ting, D. Y., Lipsitz, S. R., Ramelson, H., Suric, V., & Bates, D. W. (2016). Awareness and use of the after-visit summary through a patient portal: Evaluation of patient characteristics and an application of the theory of planned behavior. *Journal of Medical Internet Research*, *18*(4), e77.

Emotion. (n.d.). In *Merriam-Webster Dictionary*. Retrieved from shorturl.at/jBCI0

Festinger, L. (1957). *Cognitive dissonance theory*. Palo Alto, CA: Stanford University Press.

Fornell, C., & Larcker, D. F. (1981). Structural equation models with unobservable variables and measurement error: Algebra and statistics. *Journal of Marketing Research*, *18*(3), 382-388.

Fowles, J. B., Kind, A. C., Craft, C., Kind, E. A., Mandel, J. L., & Adlis, S. (2004). Patients' interest in reading their medical record: Relation with clinical and sociodemographic characteristics and patients' approach to health care. *Archives of Internal Medicine*, *164*(7), 793-800.

Frijda, N. H. (1994). Varieties of affect: Emotions and episodes, moods, and sentiments. In P. Ekman & R. Davidson (Eds.), *The nature of emotions: Fundamental questions* (pp. 59-67). Oxford, UK: Oxford University Press.

Gaskin, J., Godfrey, S., & Vance, A. (2018). Successful system use: It's not just who you are, but what you do. *AIS Transactions on Human-Computer Interaction*, *10*(2), 57-81.

Gefen, D., & Straub, D. W. (2005). A practical guide to factorial validity using PLS-graph: Tutorial and annotated example. *Communications of the Association for Information Systems*, *16*, 91-109.

Gefen, D., Straub, D. W., & Boudreau, M.-C. (2000). Structural equation modeling and regression: Guidelines for research practice. *Communication of the Association for Information Systems*, *4*, 1-77.

Glaser, J., Henley, D. E., Downing, G., & Brinner, K. M., & Personalized Health Care Workgroup of the American Health Information Community. (2008). Advancing personalized health care through health information technology: An update from the American Health Information Community's Personalized Health Care Workgroup. *Journal of the American Medical Informatics Association*, *15*(4), 391-396.

Goel, M. S., Brown, T. L., Williams, A., Cooper, A. J., Hasnain-Wynia, R., & Baker, D. W. (2011a). Patient reported barriers to enrolling in a patient portal. *Journal of the American Medical Informatics Association*, *18*, i8-i12.

Goel, M. S., Brown, T. L., Williams, A., Hasnain-Wynia, R., Thompson, J. A., & Baker, D. W. (2011b). Disparities in enrollment and use of an electronic patient portal. *Journal of General Internal Medicine*, *26*(10), 1112-1116.

Goodhue, D. L., & Thompson, R. L. (1995). Task-technology fit and individual performance. *MIS Quarterly*, *19*(2), 213-236.

Gross, J. J., & Muñoz, R. F. (1995). Emotion regulation and mental health. *Clinical Psychology: Science and Practice*, *2*(2), 151-164.

Gruzd, A. (2013). Emotions in the twitterverse and implications for user interface design. *AIS Transactions on Human-Computer Interaction*, *5*(1), 42-56.

Gu, L., & Wang, J. (2009). A study of exploring the "big five" and task technology fit in Web-based decision support systems. *Issues in Information Systems*, *10*(2), 210-217.

Haenlein, M., & Kaplan, A. M. (2004). A beginner's guide to partial least squares analysis. *Understanding Statistics*, *3*(4), 283-297.

Han, J. Y., Shaw, B. R., Hawkins, R. P., Pingree, S., McTavish, F., & Gustafson, D. H. (2008). Expressing positive emotions within online support groups by women with breast cancer. *Journal of Health Psychology*, *13*(8), 1002-1007.

Heath, S. (2018a). Patient portal access, use reach 52% of healthcare consumers. *Patient EngagementHIT.* Retrieved from https://patientengagementhit.com/news/patient-portal-access-use-reach-52-of-healthcare-consumers

Heath, S. (2018b). Patient portal adoption tops 90%, but strong patient use is needed. *Patient EngagementHIT.* Retrieved from https://patientengagementhit.com/news/patient-portal-adoption-tops-90-but-strong-patient-use-is-needed

Herath, T., & Rao, H. R. (2009). Protection motivation and deterrence: A framework for security policy compliance in organisations. *European Journal of Information Systems*, *18*(2), 106-125.

HHS. (1996). *The Health Insurance Portability and Accountability Act of 1996* (HIPAA). Retrieved from *http://www.hhs.gov/hipaa*

Hochschild, A. R. (2012). *The managed heart: Commercialization of human feeling*. Berkeley, CA: University of California Press.

Houston, T. K., & Allison, J. J. (2002). Users of Internet health information: differences by health status. *Journal of Medical Internet Research*, *4*(2), 1-15.

Hsu, J., Huang, J., Kinsman, J., Fireman, B., Miller, R., Selby, J., & Ortiz, E. (2005). Use of e-Health services between 1999 and 2002: A growing digital divide. *Journal of the American Medical Informatics Association*, *12*(2), 164-171.

Hung, S.-Y., Tsai, J. C.-A., & Chuang, C.-C. (2014). Investigating primary health care nurses' intention to use information technology: An empirical study in Taiwan. *Decision Support Systems*, *57*, 331-342.

Hunsinger, M., Poirier, C. R., & Feldman, R. S. (2008). The roles of personality and class size in student attitudes toward individual response technology. *Computers in Human Behavior*, *24*(6), 2792-2798.

Huvila, I., Enwald, H., Eriksson-Backa, K., Hirvonen, N., Nguyen, H., & Scandurra, I. (2018). Anticipating ageing: Older adults reading their medical records. *Information Processing & Management*, *54*(3), 394-407.

Johnston, A. C., & Warkentin, M. (2010). Fear appeals and information security behaviors: An empirical study. *MIS Quarterly*, *34*(3), 549-566.

Judge, T. A., Jackson, C. L., Shaw, J. C., Scott, B. A., & Rich, B. L. (2007). Self-efficacy and work-related performance: the integral role of individual differences. *Journal of Applied Psychology*, *92*(1), 107-127.

Judge, T. A., Locke, E. A., & Durham, C. C. (1997). The dispositional causes of job satisfaction: A core evaluations approach. *Research in Organizational Behavior*, 19, 151-188.

Jung, M.-L., & Loria, K. (2010). Acceptance of Swedish e-health services. *Journal of Multidisciplinary Healthcare*, 3, 55-63.

Junglas, I. A., Johnson, N. A., & Spitzmüller, C. (2008). Personality traits and concern for privacy: An empirical study in the context of location-based services. *European Journal of Information Systems*, *17*(4), 387-402.

Kaelber, D. C., Jha, A. K., Johnston, D., Middleton, B., & Bates, D. W. (2008). A research agenda for personal health records (PHRs). *Journal of the American Medical Informatics Association*, *15*(6), 729-736.

Kim, D. J., Ferrin, D. L., & Rao, H. R. (2008). A trust-based consumer decision-making model in electronic commerce: The role of trust, perceived risk, and their antecedents. *Decision Support Systems*, *44*(2), 544-564.

Kim, J., & Park, H.-A. (2012). Development of a health information technology acceptance model using consumers' health behavior intention. *Journal of Medical Internet Research*, *14*(5), e133.

Ko, M., Mancha, R., Beebe, N., & Yoon, H. S. (2012). Customers' personality, their perceptions, and green concern on internet banking use. *Journal of Information Technology Management*, *23*(4), 21-32.

Kock, N. (2019). *WarpPLS user manual* (ver. 6). Laredo, TX: ScriptWarp Systems.

Kock, N., & Moqbel, M. (2019). Social networking site use, positive emotions, and job performance. *Journal of Computer Information Systems*,

Kock, N., Moqbel, M., Barton, K., & Bartelt, V. (2016). Intended continued use of social networking sites: effects on job satisfaction and performance. *International Journal of Virtual Communities and Social Networking*, *8*(2), 28-46.

Korukonda, A. R. (2007). Differences that do matter: A dialectic analysis of individual characteristics and personality dimensions contributing to computer anxiety. *Computers in Human Behavior*, *23*(4), 1921-1942.

Korzaan, M. L., & Boswell, K. T. (2008). The influence of personality traits and information privacy concerns on behavioral intentions. *Journal of Computer Information Systems*, *48*(4), 15-24.

Kulik, J. A., & Mahler, H. I. (1987). Health status, perceptions of risk, and prevention interest for health and nonhealth problems. *Health Psychology*, *6*(1), 15-27.

Landers, R. N., & Lounsbury, J. W. (2006). An investigation of Big Five and narrow personality traits in relation to Internet usage. *Computers in Human Behavior*, *22*(2), 283-293.

Lazard, A. J., Watkins, I., Mackert, M. S., Xie, B., Stephens, K. K., & Shalev, H. (2016). Design simplicity influences patient portal use: The role of aesthetic evaluations for technology acceptance. *Journal of the American Medical Informatics Association*, *23*(e1), e157-e161.

Lemire, M., Paré, G., Sicotte, C., & Harvey, C. (2008). Determinants of Internet use as a preferred source of information on personal health. *International Journal of Medical Informatics*, *77*(11), 723-734.

Leventhal, H., Meyer, D., & Nerenz, D. (1980). The common sense representation of illness danger. *Contributions to Medical Psychology*, *2*, 7-30.

Li, H., Gupta, A., Zhang, J., & Sarathy, R. (2014). Examining the decision to use standalone personal health record systems as a trust-enabled fair social contract. *Decision Support Systems*, *57*, 376-386.

Loewenstein, G. (2005). Hot-cold empathy gaps and medical decision making. *Health Psychology*, *24*, S49-S56.

Lowry, P., Gaskin, J., & Moody, G. (2015). Proposing the multi-motive information systems continuance model (MISC) to better explain end-user system evaluations and continuance intentions. *Journal of the Association for Information Systems*, *16*(7), 515-579.

Luo, X., Warkentin, M., & Li, H. (2013). Understanding technology adoption trade-offs: A conjoint analysis approach. *Journal of Computer Information Systems*, *53*(3), 65-74.

Lu, X., & Zhang, R. (2019). Impact of physician-patient communication in online health communities on patient compliance: Cross-sectional questionnaire study. *Journal of Medical Internet Research, 21*(5), e12891.

McCrae, R. R., & John, O. P. (1992). An introduction to the five-factor model and its applications. *Journal of Personality*, *60*(2), 175-215.

McDougall, W. (1932). Of the words character and personality. *Journal of Personality, 1*(1), 3-16.

McElroy, J. C., Hendrickson, A. R., Townsend, A. M., & DeMarie, S. M. (2007). Dispositional factors in internet use: personality versus cognitive style. *MIS Quarterly*, *31*(4), 809-820.

Moore, K., & McElroy, J. C. (2012). The influence of personality on Facebook usage, wall postings, and regret. *Computers in Human Behavior*, *28*(1), 267-274.

Moqbel, M., & Iftab, F. (2015). Employees' social networking site use impact on job performance: Evidence from Pakistan. *AIS Transactions on Replication Research*, *1*(6), 1-10.

Moqbel, M., & Nah, F. F.-H. (2017). Enterprise social media use and impact on performance: The role of workplace integration and positive emotions. *AIS Transactions on Human-Computer Interaction*, *9*(4), 261-280.

Moqbel, M., Nevo, S., & Kock, N. (2013). Organizational members' use of social networking sites and job performance: An exploratory study. *Information Technology & People*, *26*(3), 240-264.

Nicholas, D., Huntington, P., & Williams, P. (2003). Three years of digital consumer health information: A longitudinal study of the touch screen health kiosk. *Information Processing & Management*, *39*(3), 479-502.

Osatuyi, B. (2015). Personality traits and information privacy concern on social media platforms. *Journal of Computer Information Systems*, *55*(4), 11-19.

Patel, V., Barker, W., & Siminerio, E. (2015). Trends in consumer access and use of electronic health information. *U.S. Department of Health and Human Services.* Retrieved from https://dashboard.healthit.gov/evaluations/data-briefs/trends-consumer-access-use-electronic-health-information.php

Patel, V., & Johnson, C. (2018). Individuals' use of online medical records and technology for health needs. *The Office of the National Coordinator for Health Information Technology.* Retrieved from https://www.healthit.gov/sites/default/files/page/2018-03/HINTS-2017-Consumer-Data-Brief-3.21.18.pdf

Petrie, K. J., Weinman, J., Sharpe, N., & Buckley, J. (1996). Role of patients' view of their illness in predicting return to work and functioning after myocardial infarction: Longitudinal study. *British Medical Journal, 312*(7040), 1191-1194.

Petty, R. E., & Cacioppo, J. T. (1986). The elaboration likelihood model of persuasion. In R. E. Petty & J. T. Cacioppo (Eds.), *Communication and persuasion*. New York, NY: Springer.

Pires, G., Stanton, J., & Eckford, A. (2004). Influences on the perceived risk of purchasing online. *Journal of Consumer Behaviour*, *4*(2), 118-131.

Portz, J. D., Bayliss, E. A., Bull, S., Boxer, R. S., Bekelman, D. B., Gleason, K., & Czaja, S. (2019). Using the technology acceptance model to explore user experience, intent to use, and use behavior of a patient portal among older adults with multiple chronic conditions: Descriptive qualitative study. *Journal of Medical Internet Research*, *21*(4), p. e11604.

Pugh, S. D., Groth, M., & Hennig-Thurau, T. (2011). Willing and able to fake emotions: A closer examination of the link between emotional dissonance and employee well-being. *Journal of Applied Psychology*, *96*(2), 377-390.

Rahman, M. S. (2015). *Understanding factors influencing intention to use electronic health records (EHRs): An integration of multiple theoretical perspectives* (doctoral dissertation). The University of Texas at San Antonio, San Antonio, TX.

Robert, L. P., Pierce, C., Marquis, L., Kim, S., & Alahmad, R. (2020b). Designing fair AI for managing employees in organizations: A review, critique, and design agenda. *Human-Computer Interaction*, 1-31.

Robert, L., Alahmad, R., Zhang, Q., Kim, S., Esterwood, C., & You, S. (2020a). A review of personality in human robot interactions. *Foundations and Trends in Information Systems*, *4*(2), 107-212.

Robey, D. (1983). Cognitive style and DSS design: A comment on Huber's paper. *Management Science*, *29*(5), 580-582.

Robey, D., & Markus, M. L. (1984). Rituals in information system design. *MIS Quarterly*, *8*(1), 5-15.

Roblin, D. W., Houston, T. K., Allison, J. J., Joski, P. J., & Becker, E. R. (2009). Disparities in use of a personal health record in a managed care organization. *Journal of the American Medical Informatics Association*, *16*(5), 683-689.

Rogers, E. M. (1995). *Diffusion of innovations*. New York, NY: Free Press.

Ross, C., Orr, E. S., Sisic, M., Arseneault, J. M., Simmering, M. G., & Orr, R. R. (2009). Personality and motivations associated with Facebook use. *Computers in Human Behavior*, *25*(2), 578-586.

Saleem, H., Beaudry, A., & Croteau, A.-M. (2011). Antecedents of computer self-efficacy: A study of the role of personality traits and gender. *Computers in Human Behavior*, *27*(5), 1922-1936.

Sarkar, U., Karter, A. J., Liu, J. Y., Adler, N. E., Nguyen, R., López, A., & Schillinger, D. (2010). The literacy divide: Health literacy and the use of an Internet-based patient portal in an integrated health system—results from the Diabetes Study of Northern California (DISTANCE). *Journal of Health Communication*, *15*, 183-196.

Sarkar, U., Karter, A. J., Liu, J. Y., Adler, N. E., Nguyen, R., López, A., & Schillinger, D. (2011). Social disparities in internet patient portal use in diabetes: Evidence that the digital divide extends beyond access. *Journal of the American Medical Informatics Association*, *18*(3), 318-321.

Schachter, S., & Singer, J. (1962). Cognitive, social, and physiological determinants of emotional state. *Psychological Review*, *69*(5), 379-399.

Schnipper, J. L., Gandhi, T. K., Wald, J. S., Grant, R. W., Poon, E. G., Volk, L. A., Businger, A., Siteman, E., Buckel, L., & Middleton, B. (2008). Design and implementation of a Web-based patient portal linked to an electronic health record designed to improve medication safety: The Patient Gateway medications module. *Informatics in Primary Care*, *16*(2), 147-155.

Tavares, J., & Oliveira, T. (2016). Electronic health record patient portal adoption by health care consumers: An acceptance model and survey. *Journal of Medical Internet Research*, *18*(3), e49.

Thatcher, J. B., & Perrewe, P. L. (2002). An empirical examination of individual traits as antecedents to computer anxiety and computer self-efficacy. *MIS Quarterly*, *26*(4), 381-396.

Tooby, J., & Cosmides, L. (2000). Evolutionary psychology and the emotions. M. Lewis, J. M. Haviland-Jones, & L. F. Barrett (Eds.), *Handbook of emotions* (p. 114-137). New York, NY: The Guilford Press.

Trumbo, C. W., McComas, K. A., & Kannaovakun, P. (2007). Cancer anxiety and the perception of risk in alarmed communities. *Risk Analysis: An International Journal*, *27*(2), 337-350.

Tulving, E. (1983). *Elements of episodic memory*. New York, NY: Oxford University Press.

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

Watson, D., & Clark, L. A. (1997). Extraversion and its positive emotional core. In R. Hogan, J. A. Johnson, & S. R. Briggs (Eds.), *Handbook of personality psychology* (pp. 767-793). San Diego, CA: Academic Press

Weingart, S. N., Rind, D., Tofias, Z., & Sands, D. Z. (2006). Who uses the patient internet portal? The PatientSite experience. *Journal of the American Medical Informatics Association*, *13*(1), 91-95.

Wilson, V., & Djamasbi, S. (2015). Human-computer interaction in health and wellness: Research and publication opportunities. *AIS Transactions on Human-Computer Interaction*, *7*(3), 97-108.

Wilson, V., & Lankton, N. K. (2004). Modeling patients' acceptance of provider-delivered e-health. *Journal of the American Medical Informatics Association*, *11*(4), 241-248.

Wyatt, K., & Phillips, J. G. (2005). Internet use and misuse in the workplace. In *Proceedings of the 17th Australia Conference on Computer-Human Interaction*.

Xiao, N., Sharman, R., Rao, H., & Upadhyaya, S. (2014). Factors influencing online health information search: An empirical analysis of a national cancer-related survey. *Decision Support Systems*, 57, 417-427.

Yoon, H. S., & Steege, L. M. B. (2013). Development of a quantitative model of the impact of customers' personality and perceptions on Internet banking use. *Computers in Human Behavior*, *29*(3), 1133-1141.

Yuan, L., & Dennis, A. (2016). The happiness premium: The impact of emotion on individuals' willingness to pay in online auctions. *AIS Transactions on Human-Computer Interaction*, *8*(3), 74-87.

Zhou, T., & Lu, Y. (2011). The effects of personality traits on user acceptance of mobile commerce. *International Journal of Human-Computer Interaction*, *27*(6), 545-561.

Zmud, R. W. (1979). Individual differences and MIS success: A review of the empirical literature. *Management Science*, *25*(10), 966-979.

Appendix A: Construct Measurement Instrument

We used the questions below to collect data related to the indicators of the latent variables. We used a Likert-type scale for the questions (1 = strongly disagree, 5 = strongly agree).

Health emotion (HE)

HE1: I am unhappy about the present state of my health.

HE2(R): In general, I consider my current health to be excellent.

Extraversion (EXT)

EXT1: I consider myself as someone who is talkative.

EXT2: I consider myself as someone who is outgoing.

EXT3: I feel comfortable around people.

EXT4(R): I don't like to draw attention to myself.

Neuroticism (NEU)

NEU1: I get nervous easily.

NEU2: I worry about things a lot.

NEU3: I change my mood a lot.

Conscientiousness (CON)

CON1: I consider myself as reliable/dependable.

CON2: I like to pay attention to details.

CON3: I like to make plans and follow through.

CON4: I like to do things efficiently.

Openness to experience (OTE)

OTE1: I always have new ideas.

OTE2: I consider myself open to new experiences.

OTE3: I am quick to understand things.

OTE4(R): I am generally hesitant to try out new technology.

Agreeableness (AGR)

AGR1: I consider myself as helpful and unselfish with others.

AGR2: I sympathize with others' feelings.

AGR3: I generally consider myself a trusting person.

AGR4: I like to make people feel at ease.

Intended continuous use (ICU)

IU1: I would use a patient portal for my future healthcare needs.

IU2: I intend to use the patient portal in the following weeks.

About the Authors

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