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# Understanding Online Health Information Use: The Case of People with Physical Disabilities

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## Abstract:

In this paper, we study the online health information use behavior of people with physical disabilities. Drawing on rational choice theory and IS success model, we develop a contextualized research model to explain how individuals' level of physical disability moderates the effects of object- and outcome-based beliefs. We empirically tested the model with survey data from 243 online users with physical disabilities. The results show that perceived benefit enhances, whereas perceived risk reduces, online health information use. Information quality and system quality increase perceived benefit and mitigate perceived risk. In addition, we found that accuracy, completeness, currency, and transparency of online health information predict information quality, whereas accessibility, navigability, and readability of online health information predict system quality. More importantly, we found that physical disability weakens the effect of information quality on perceived risk, strengthens the effect of system quality on perceived risk, and strengthens the effect of perceived benefits on information use. This research contributes to the IS literature by focusing on the minority group of people with physical disabilities and providing an in-depth understanding of their online health information use behavior.

**Keywords:** Physical Disability, Information Quality, System Quality, Perceived Benefit, Perceived Risk.

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# 1 Introduction

In this paper, we investigate antecedents of the online health information use behavior of people with physical disabilities by drawing from the IS success model (Delone & McLean, 1992) and rational choice theory (Mellers, Schwartz, & Cooke, 1998). We define online health information use as the actual integration of the health information acquired from the Internet into an individual's health-related behaviors such as decision making, care seeking, and/or behavior change. While research has paid much attention to the seeking of online health information (Cline & Haynes 2001; Liang, Xue, & Chase, 2011; Miller & Bell, 2012; Powell, Inglis, Ronnie, & Large, 2011; Rice, 2006; Weaver et al. 2010), relatively few studies have investigated the usage of such information. Information use is a critical step subsequent to information seeking because people often must do something with the information they receive to attain their goals (Dennis, 1996). Online health information use is particularly important for people with disabilities because they have difficulties in accessing normal social life and healthcare (Brault, 2012; CDC, 2011; NCD, 2009; WHO, 2011). Research has found that, compared with their healthy peers, people with disabilities are more likely to seek online health information and use it to inform their health-related decisions (Fox, 2007). However, little research has examined why and how they use online health information. While rational choice theory predicts individuals' use of online health information based on a risk benefit analysis (Mellers et al., 1998) and the IS success model suggests how information- and system-related characteristics affect such usage (Delone & McLean, 1992), it is unclear whether these theoretical premises are still valid when people with physical disabilities are the research subjects. Disability scholars suggest that applying behavioral theories to people with disabilities should be carefully examined because of the unique personal and environmental characteristics of these people (Ravesloot et al., 2011). Thus, we lack a theoretical explanation of online health information use by people with physical disabilities. To fill this gap in the literature, we propose a research model that highlights the level of physical disability as a moderator and empirically test it using survey data.

This paper makes four contributions. First, it focuses on a minority group: people with physical disabilities, whom information systems (IS) researchers have largely neglected. While this group faces tougher challenges when they use IT than average users, in reviewing the literature, we found that few IS researchers have examined their interaction with IT. This research raises awareness to this disadvantaged group and can help explain the disparity issues caused by physical disabilities. Second, this research integrates IS success model and rational choice theory to develop a strong theoretical foundation on which we investigate online health information use. We identify a group of system characteristics that affect the quality perceptions of online health information. One can use these characteristics to design effective strategies to provide online health information to people with physical disabilities who need more assistance than regular users (W3C, 2013a). Third, this research focuses on the information use behavior rather than information seeking or intention to use. Health information has little impact on people's health unless they use it in some form. Fourth, this research investigates the moderating role of physical disability, which helps to explain the uniqueness of IT behaviors of people with disabilities. Overall, this research contributes to theory of individual IS use by extending the target users to people with physical disabilities and contributes to practice by offering implications about how to protect the wellbeing of people with physical disabilities through appropriate online health information use.

This paper proceeds as follows: in Section 2, we provide more information of physical disability and online health information. In Section 3, we develop the research model and hypotheses. In Section 4, we describe the method and, in Section 5, the results. Finally, in Section 6, we discuss the findings, their implications, and limitations.

# 2 Physical Disability and Online Health Information

Disability refers to "any restriction or lack (resulting from an impairment) of ability to perform an activity in the manner or within the range considered normal for a human being" (United Nations, 2015). The World Health Organization estimates that the worldwide disability prevalence is 15 percent; that is, more than a billion people have some form of disability (WHO, 2011). According to the U.S. Census Bureau, there are about 56.7 million (or almost 20 percent) of Americans who live with a disability (The Census Bureau, 2014). As technology and medicine advance, people live longer and are more likely to develop chronic diseases and disabilities than before. The census data shows that the disability prevalence for American people aged 65 and older jumps from 20 percent to an alarming 49.8 percent (Brault, 2012).

While one can classify disabilities into various categories based on different schemes, in this paper, we focus on physical disabilities[1]. The U.S. Census Bureau specifically defines physical disability as an individual who has difficulty in performing physical activities such as walking, climbing stairs, lifting heavy groceries, or getting in and out of bed due to physical impairments or medical conditions (Brault, 2012). Physical disability is the most prevalent form of disability in the US and affects more than 30.6 million Americans (The Census Bureau, 2014). It poses a great barrier to regular education, employment, and social life (Brault, 2012; CDC, 2011; WHO, 2011). Ironically, despite being those with great need, it is particularly difficult for people with disabilities to access healthcare (NCD, 2009). People with physical disabilities experience a significantly reduced quality of life because of their restricted accessibility to physical and social environments (Brault, 2012). The Internet can play an important role in improving their access to the external resources and affording them equal opportunities (Fox, 2007).

The Internet has become indispensable to our lives with the tremendous diffusion of social media and a variety of online support groups. Online health information seeking is one of the most performed online activities (Miller & Bell, 2012; Rice, 2006). The 2012 U.S. census data shows that over 98 percent of Americans have Internet access (NITA, 2013). The Pew/Internet survey shows that 72 percent of American Internet users and 59 percent of all American adults searched for some health-related information online in the past 12 months (Fox & Duggan, 2013). Internet users seek information on several health topics ranging from diet and exercise to specific medications and diseases. Over half (59%) online health information seekers indicate that the information has helped them self-diagnose their medical conditions (Fox & Duggan, 2013). The Internet is a particularly valuable health information resource for people with physical disabilities due to the challenges for these people to access traditional information sources (e.g., physician office) that require mobility. Compared to other Internet users, users with physical disabilities are more likely to search online health information, and the information is more likely to influence their medical treatment decisions (Fox, 2007). Specifically, 86 percent of Internet users with disabilities have sought health information online and 75 percent have integrated the health information into their medical treatment decisions (Fox, 2007). It is obvious that online health information seeking is prevalent among physically disabled Internet users and that this behavior could have a significant impact on these users' health outcomes.

# 3 Research Model and Hypotheses

## 3.1 Theoretical Framework

We draw on rational choice theory (Mellers et al., 1998) and the IS success model (Delone & McLean, 1992) to explain the online health information use of people with physical disabilities. In the healthcare context, especially when people with physical disabilities who likely have chronic conditions such as diabetes and arthritis (Reichard, Stolzle, & Fox, 2011) are involved, information use is a highly important behavior that bears significant implications for patient health and wellbeing. Health information could generate a concrete impact on an individual's physiological or psychological health after it is used to change or guide the individual's health-related decisions and behaviors. In the existing healthcare system in the US, the continuity of care for physically disabled and chronically ill patients is suboptimal because the system is designed to provide acute and episodic care in disparate facilities (Anderson & Knickman, 2001). Since primary care doctors have limited time to see patients, patient self-management has been widely advocated and practiced to treat chronic conditions (Bodenheimer, Wagner, & Grumbach, 2002; Lorig & Holman, 2003). In order to be capable of performing self-management, patients must have sufficient knowledge and information in the relevant medical domain. Thus, patients' help themselves by using online health information could have a tremendous impact on their disease management and health outcomes (Song & Zahedi, 2007; Zahedi & Song, 2008). However, we know little about why people with physical disabilities use online health information and what factors influence the use. In this paper, we propose that integrating rational choice theory and the IS success model can explain these questions.

Rational choice theory (RCT) posits that, before deciding on an action, individuals appraise the risks and benefits of available options and prefer the one that generates the maximum utility. RCT has long been the dominant decision framework in psychology, economics, political science, finance, marketing, and

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[1] People with physical disabilities have normal sensory and cognitive functions that were essential for them to participate in our study. People with sensory disabilities (e.g., blindness and deafness) or cognitive disabilities (e.g., autism or retardation) would have had great difficulty in participating in our study. In addition, people with cognitive disabilities cannot independently use online health information and, thus, were ineligible for our study.

criminology (Mellers et al., 1998). IS researchers have also applied to explain individuals' security behavior (e.g., Aytes & Terry, 2004; Bulgurcu, Cavusoglu, & Benbasat, 2010). While seeking health information and following health advice from the Internet bring many benefits such as convenience, low cost, and anonymity for sensitive questions, it is also fraught with potential risks such as inaccurate diagnosis and misleading advice that could lead to delayed treatment and illness exacerbation (Eysenbach, Powell, Kuss, & Sa, 2002; Killeen et al., 2011). Therefore, individuals must compare the gains and losses associated with online health information, and whether to use the information is a decision based on an approximate risk benefit analysis. Rational choice theory (Mellers et al., 1998) offers reasonable explanations for this human behavior. In the rational choice framework, individuals identify their behavioral alternatives and evaluate the possible outcomes of each alternative. They determine the utility of each outcome by how many risks and benefits it brings to them. By comparing the overall utility of each behavioral option, individuals will be able to decide which one is the best for them. Based on RCT, we can identify perceived benefit and perceived risk as two basic outcome-based beliefs that affect an individual's use of online health information.

The IS success model is a comprehensive, multi-dimensional framework for evaluating IS success (Delone & McLean, 1992, 2003). The original model suggests that one can assess IS success by considering six dimensions: system quality, information quality, use, user satisfaction, individual impact, and organizational impact. Causal relationships exist among these dimensions: system quality and information quality lead to higher user satisfaction and system use, which enhances individual productivity and improves organizational performance. While the IS success model focuses on the organizational context, researchers have applied its propositions related to individual behaviors to the context of individual IT use (Petter, DeLone, & McLean, 2008; Rai, Lang, & Welker, 2002). It posits that system quality and information quality are user beliefs based on technological features and functionalities of information systems and that these beliefs are the primary causes of user behavior and satisfaction (Delone & McLean, 1992). In the context of online health information use, system quality refers to the capabilities of the Internet mechanisms that support an individual's searching, identifying, acquiring, and understanding relevant health information, and information quality refers to the degree to which individuals believe that the health information obtained from the online environment is high quality. Following Wixom and Todd (2005), we label these two concepts as object-based beliefs because they are based on objective system and information characteristics.

Both the IS success model and RCT explain individuals' IT behavior and provide complementary perspectives. RCT focuses on individuals' rational judgments of costs and benefits of behavioral choices but does not show how these judgments are influenced by their beliefs of the IT artifacts: system and information. IS success model emphasizes the relationship between object-based beliefs and the use behavior but is silent on how system and information quality lead to outcome-based judgments and decisions. A weakness of the object-based beliefs is that they have limited power to predict usage behavior (Delone & McLean, 1992; Seddon, 1997). Wixom and Todd (2005) have theoretically articulated and empirically shown that object-based beliefs are distal predictors of behavior and that outcome-based beliefs mediate their effects. A meta-analysis also shows that the relationship between information quality and use is insufficiently supported and that there is mixed support for the relationship between system quality and use (Petter et al., 2008). In contrast, a problem of the outcome-based beliefs is that they are based on general perceptions of IT artifacts and cannot provide insights for system design and development. Venkatesh, Morris, Davis, and Davis (2003) have emphasized the necessity of explicitly studying system and information characteristics' direct impact on user beliefs and indirect impact on usage behaviors. Therefore, it is theoretically justified and desirable to integrate RCT and the IS success model to create a more holistic explanation of individuals' online health information use behavior. As Figure 1 shows, in our integrated research model, information and system quality are object-based beliefs that a set of perceived object characteristics determine: the object-based beliefs influence outcome-based beliefs including perceived benefit and risk of using online health information, and outcome-based beliefs lead to individuals' information use. In addition, to understand how our unique research context alters the applicability of theory, we propose that individuals' physical disability level plays a moderating role between object-based and outcome-based beliefs and between outcome-based beliefs and information use behavior.

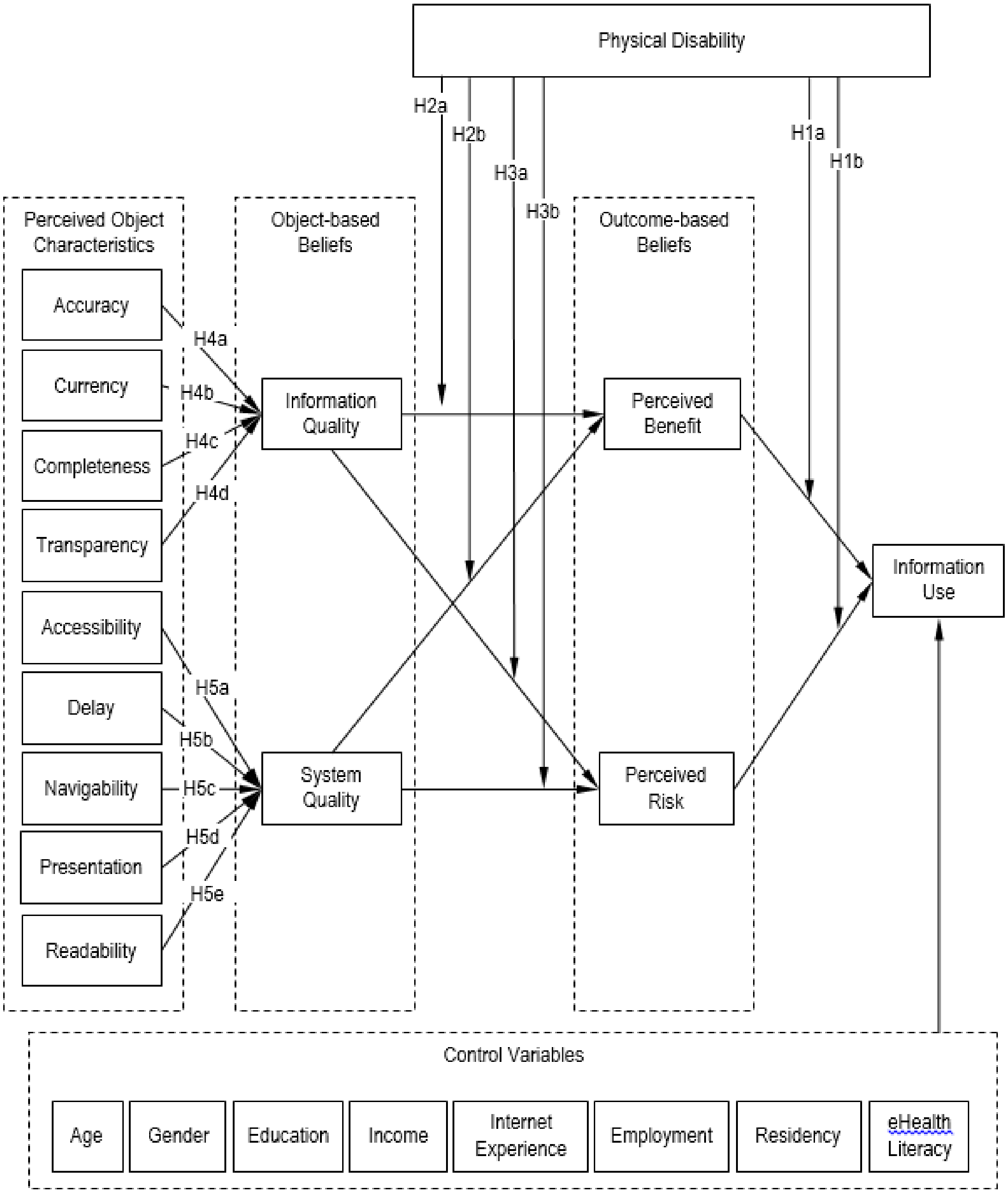

**Figure 1. Research Model**

## 3.2 Hypothesis Development

We assume that people with physical disabilities search for online health information because they need to use the information to cope with a health-related issue (about, for example, medications, diseases, diet, exercise, self-care, and so on) (Cline & Haynes, 2001; Fox, 2006; O'Connor & Johanson, 2000). Individuals will not use all of the health information they obtain from the Internet. Before individuals decide whether to use a piece of online health information, they normally follow a rational approach to evaluate the potential benefits and risks of doing so. One can expect online health information to be valuable for patients given that it could contribute to patient health in several ways, such as enhancing their knowledge and understanding about their conditions, empowering them to perform self-care and engage in healthy behaviors, assisting them to effectively communicate with physicians and participate in their care plan, and supporting their decision making about treatment options (Baker, Wagner, Singer, & Bundorf, 2003;

Rice, 2006). These potential benefits can be a motivating force that drives people with physical disabilities to use online health information. Thus, we expect a positive relationship between perceived benefit and online health information use.

Perceived benefit refers to the extent to which individuals believe that using online health information will benefit them. The main effect of perceived benefit could vary at different levels of physical disabilities and give rise to an interesting moderation effect. Physical disabilities not only cause physical inconvenience but also give rise to a social exclusion effect (Harris, 2000). The existing policies and facilities that societies provide are inadequate to help people with disabilities enjoy equal opportunities (Fine & Asch, 1988). People with disabilities are often seen as abnormal and seriously stigmatized (Link & Phelan, 2001). As a result, these people are unable or unwilling to receive support from society. As their physical disability level heightens, the lack of support worsens. Online health information could empower these people to cope with problems they encounter on a daily basis (through, for example, social media and online support groups) (Davison, Pennebaker, & Dickerson, 2000). Such benefits are particularly important to people with more severe physical disabilities because, compared with the less severely disabled, they have more limited means to get help. Therefore, the relationship between perceived benefits of online health information and the behavior of using this information will become stronger as the disability level increases.

**H1a:** Physical disability strengthens the positive relationship between perceived benefit and online health information use.

Online health information has an uncertain quality. Despite the existence of high-quality online health information, much online health information could be irrelevant, inaccurate, or misleading and, hence, physical, emotional, and financial damages could result (Eysenbach et al., 2002; Killeen et al., 2011). To make things worse, many fake websites provide false, fictitious, biased, or misleading information about nutrition, exercise, diet, medications, surgery, and miracle remedies and can be used to commit medical identity theft (Abbasi, Zahedi, & Kaza, 2012). For example, rogue Internet pharmacies often disguise themselves as legitimate pharmacies but sell substandard or counterfeit pharmaceuticals. Consumers who have been deceived by the false information these pharmacies presented and take their pharmaceuticals have experienced health issues, needed emergency treatments, and even died (Government Accountability Office, 2013). Gyongyi and Garcia-Molina (2005) estimate that fake websites represent almost 20 percent of the Web. Clearly, a substantial amount of risks are associated with using online health information. Rational choice theory (Mellers et al., 1998) suggests individuals evaluate both benefits and risks related to online health information use, and researchers have long known that people are motivated to approach gains and avoid losses (Kahneman & Tversky, 1979; Liang & Xue, 2009). Prior research shows that individual IT users in general have a tendency to achieve utilitarian goals and evade risks and uncertainties (e.g., Liang & Xue, 2009; Pavlou, 2003; Pavlou, Liang, & Xue, 2007). Research has found that risk perceptions have a negative impact on individuals' intention to use online health information in their health decisions (Song & Zahedi, 2007). Therefore, we expect a negative relationship between perceived risk and online health information use.

Following Pavlou (2003) and Song and Zahedi (2007), we define perceived risk as the extent to which personal losses or negative consequences result from using online health information. In this paper, we further contend that the main effect of perceived risk depends on the level of one's physical disability. Physical disability creates a great deal of stress that has to be dealt with on a daily basis because people with physical disabilities commonly experience negative emotions such as depression, anxiety, and anger (Livneh & Antonak, 1991; Ormel et al., 1994). Research has found that these negative emotions are long term and unlikely to subdue over time (Treharne, Lyons, Booth, Mason, & Kitas, 2004). The cumulative evidence in neuropsychology literature shows that stress influences cognition by changing dopamine in certain brain regions; specifically, stress enhances approach to positive outcomes and impairs avoidance of negative outcomes (Mather & Lighthall, 2012). Clinical evidence shows that, as people get older and more physically disabled, their depression and stress becomes more acute (Bruce, 2001). Influenced by acute stress, people with high physical disability tend to overweigh the perceived benefit and underestimate the perceived risk of online health information use. That is, people with severe physical disabilities are likely to ignore the potential risks when deciding whether to use online health information even though the risks could be high for them, which suggests that perceived risk has a weaker impact on information use at a high physical disability level.

**H1b:** Physical disability weakens the negative relationship between perceived risk and online health information use.

Online health information could be highly beneficial to individuals, especially those with physical disabilities who have to deal with various medical and rehabilitative challenges (Fox, 2007). High-quality online health information could help individuals effectively cope with their existing conditions or prevent potential complications. Such information could also increase individuals' medical knowledge and empower them to perform disease self-management (Barak, Boniel-Nissim, 2008; Hill, Weinert, & Cudney, 2006; Lorig, Ritter, & Laurent, 2006; Winzelberg, Classen, & Alpers, 2003). Obviously, the quality of online health information plays a critical role in determining how beneficial the information could be. While high-quality information brings benefits, low-quality information could lead to harmful consequences (Crocco, Villasis-Keever, & Jadad, 2002; Eysenbach et al., 2002; Killeen et al., 2011). Therefore, people with physical disabilities tend to expect to gain benefits from high-quality online health information, which gives to a positive relationship between information quality and perceived benefit of online health information use.

While high-quality online health information could benefit people with physical disabilities, these individuals evaluate such benefits based on the personal relevance of the information. According to relevance theory (Wilson & Sperber, 2004), an input is relevant to individuals when it integrates background information to yield outcomes that matter to them. For example, a piece of online health information is relevant to people with physical disabilities if it helps them answer questions, resolve doubts, or confirm suspicions related to physical disabilities. That is, high-quality information is only deemed beneficial when it matches the individual's needs. If an individual does not the information, the individual is unlikely to perceive as beneficial even if it is high quality. For example, information about uterine cancer will be irrelevant to a man, and, therefore, a man will likely not perceive it as beneficial (assuming he is evaluating benefits to himself only and not somebody else he cares about). People with a higher level of physical disability seek and use more online health information than those with a lower level of physical disability (Fox, 2007). When coping with increasing physical disabilities on a daily basis, individuals will encounter more questions and have a greater need of online health information to find answers (Cotten & Gupta, 2004). Thus, online health information is more personally relevant as physical disability increases. As a result, information quality has a greater effect on perceived benefit of online health information use at a higher level of physical disability.

**H2a:** Physical disability strengthens the positive relationship between information quality and perceived benefit of online health information use.

Seeking online health information incurs both cognitive and physical efforts, especially for people with physical disabilities. Websites with high system quality could make health information more available, accessible, understandable, and enjoyable and, thus, reduce the costs of finding relevant information. Based on the classic rational choice of human behaviors (Becker, 1976), as costs go down, individuals will perceive more net benefits. Moreover, although system quality concerns how online health information is retrieved and presented and not about the information content, it conveys important cues (e.g., the authority of the information source, the quality of presentation, etc.) that individuals can process to infer the information's credibility and, thus, value. Prior research has shown that message cues can increase the persuasiveness of a message although they do not relate to the message content (Chaiken, 1980). Due to knowledge barriers, average people may not be able to evaluate health information quality directly and often rely on heuristics based on peripheral cues to judge credibility of online information (Metzger, Flanagin, & Medders, 2010). Similarly, in our research context, people with physical disabilities can use system quality as cues to heuristically assess the value of online health information. High system quality engenders an impression that the information provided is also high quality and can bring benefits[2]. That is, we expect a positive relationship between system quality and perceived benefit of online health information use.

As physical disability worsens, people are more severely separated from normal social life and have greater difficulty getting health information. Since physicians have limited time to interact with patients, it is difficult for people with disabling or chronic conditions to receive adequate health information from physicians (Bodenheimer et al., 2002). Increased physical disability also makes it more difficult for an individual to access the Internet, which adds search costs to using online health information (WHO, 2011). Even a simple task for a normal person can be challenging for a disabled person. For example, it could take a long time for a Parkinson's disease patient to click on a hyperlink because of shaking hands. System quality could help to remove the additional costs and increase the net benefits of using online health information. Moreover, disability leads to great education disparity. A CDC report has shown that the high school non-completion rate of American adults with disabilities is almost twice as high as that of

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[2]

those with no disabilities (CDC, 2011). As education level decreases, people with disabilities have even greater knowledge barrier to the evaluation of online health information and tend to rely more heavily on heuristics to judge the benefits of such information. Given that system quality is an important source of cues in the online context (Metzger et al., 2010), the impact of system quality on perceived benefit of online health information use will likely be greater when the physical disability level is high.

**H2b:** Physical disability strengthens the positive relationship between system quality and perceived benefit of online health information use.

The uncertain quality of online health information has drawn alarming attention in the medical community (Eysenbach et al., 2002; Killeen et al., 2011). Many physicians have expressed concern that erroneous or misleading online health information can cause harm to patients (Crocco et al., 2002). Using online health information has a tremendous number of risks. When individuals perceive online health information to be inaccurate, incomplete, or outdated, they will reasonably worry about possible negative consequences that will result from such low-quality information. Conversely, research believes using high-quality online health information to not be risky because people perceive it as accurate (precise, no ambiguity), complete (providing alternative viewpoints, pros and cons, no hidden information), current (showing the latest findings of medical research and practice), and reliable (disclosing sponsorship, sources, and references) (Song & Zahedi, 2007). Therefore, we submit that information quality can mitigate the perceived risk of using online health information.

However, the main effect of information quality on perceived risk could decline as individuals' disability level heightens. One can explain this contingent effect from a social exclusion perspective. While research has traditionally seen physical disabilities as mostly medical or pathological problems, the new socioecological paradigm in disability research goes beyond the medical model by treating disability as a complex interaction between person and environment (Tate & Pledger, 2003). Social exclusion is a major problem associated with disability because it is common for people with disabilities to suffer from unfair treatment, discrimination, or stigmatization and, thus, have fewer opportunities to participate in normal social life (Fine & Asch, 1988; Harris, 2000; Link & Phelan, 2001). Prior psychology research has found that "physical sensation and emotional reactivity become dulled and insensitive" when a person is socially excluded (DeWall & Baumeister, 2006, p. 12). Because the emotional system is essential for rational decisions and judgments (Slovic, Finucane, Peters, & MAcGregor, 2004), people are likely to make faulty decisions and judgments when their emotional system ceases to function normally. Research has found that social exclusion leads individuals to ignore potential risks and take irrational ones (Twenge, Catanese, & Baumeister, 2002). In our research context, as people become more physically disabled, they are likely to be more socially excluded. The increased social exclusion causes emotional numbness in people with disabilities and impairs their sensitivity to risks in general and to risks of online health information use in particular. That is, they will not perceive an increase in risks even if the objective risks increase. Hence, information quality will have a weaker effect on perceived risk when physical disability is high than when it is low.

**H3a:** Physical disability weakens the negative relationship between information quality and perceived risk.

In addition to information quality, individuals can employ heuristics to "sense" potential risks by processing cues conveyed by system quality (Chaiken, 1980). For example, a website that has many broken links, sloppy texts, long delays, and overt commercialism may suggest that the website is not professionally managed, lacks healthcare expertise, or has bias in favor of certain health products and, thus, that using its health information is risky. On the contrary, high system quality can make one trust the website and believe that it is safe to use the online health information (Bart, Shankar, Sultan, & Urban, 2005; Song & Zahedi, 2007). Therefore, we expect that system quality is negatively associated with perceived risk of online health information use. Similar to the way through which physical disability moderates the relationship between information quality and perceived risk, the main effect of system quality will reduce as physical disability increases. That is, physical disability leads to social exclusion (Fine & Asch, 1988; Harris, 2000; Link & Phelan, 2001) and social exclusion results in emotional numbness (DeWall & Baumeister, 2006). As a result, individuals with physical disabilities become insensitive to changes in risk perceptions.

**H3b:** Physical disability weakens the negative relationship between system quality and perceived risk.

The IS success model suggests that the characteristics of an IT artifact determine system and information quality. Yet, it does not specify what characteristics one should consider. Drawing from prior research

(Cline & Haynes, 2001; Wixom & Todd, 2005), we identify a set of antecedents for information and system quality. We intend these antecedents to be typical for the online health information use context rather than to be comprehensive. Although they may have effects in the online information use context in general, we need to include them in our research model to form a broad nomological network so that we can fully understand their unique effects in the online health information use context.

Specifically, accuracy, currency, completeness, and transparency determine information quality. Accuracy refers to the extent to which the health information is correct or based on evidence. Currency refers to the extent to which the health information is up to date. Completeness refers to the extent to which all necessary information is presented. Transparency represents the extent to which critical supporting information is provided such as authors, sources, references, and sponsorships. Research has shown that accuracy, currency, and completeness are positively related to information quality (Wixom & Todd, 2005) and identified them as the most important design features for medical websites (Zhang, Von Dran, Blake, & Pipithsuksunt, 2001). Prior research has also found that online users are concerned about transparency (Cline & Haynes, 2001). Transparency is associated with questions such as: who created the website? Who is running the website? Who is sponsoring the website? What is the source of the information? Is the information reviewed by experts? Answers to these questions help individuals appropriately evaluate information quality. Thus, transparency signals that the online health information provider has nothing to hide. When an online information source is not transparent, there is a high level of information asymmetry between information providers and receivers. For example, a private company's website may present information that favors its own products but intentionally hide the sponsorship to make the information appear free of bias. Such information asymmetry tends to make people feel uncertain about the provider and doubt the quality of the information it provides (Liang, Xue, Laosethakul, & Lloyd, 2005; Pavlou et al., 2007).

**H4a:** Accuracy is positively associated with information quality.

**H4b:** Currency is positively associated with information quality.

**H4c:** Completeness is positively associated with information quality.

**H4d:** Transparency is positively associated with information quality.

The antecedents of system quality include accessibility, delay, navigation, presentation, and readability. Accessibility refers to the extent to which one can access or extract health information from the Internet (Wixom & Todd, 2005). Delay refers to the lag between a user request of certain health information and the system's response to the request (Galletta, Henry, McCoy, & Polak, 2006). Navigability refers to the system's capability of allowing the user to navigate among different webpages and websites (Palmer, 2002). Presentation refers to the aesthetic format in which health information is presented (Bart et al., 2005). Readability refers to the extent to which health information is written in plain language that lay people can understand. Research has recognized lack of accessibility as a major barrier for people with disabilities to take advantage of the Internet (Jaeger, 2006). Many countries around the world have enacted laws and policies to require websites to have sufficient accessibility so that all members of society, including people with disabilities, have equal opportunity to access the information medium (W3C, 2013b). Prior research has found that website delays dampen users' intention to continue interacting with them (Galletta et al., 2006). The longer the delay, the more likely will users leave the website. Research has found navigability to be an important metric for website design, and successful websites tend to have a high level of navigation features (Palmer, 2002). For online health information, research has applied presentation and readability as the basic design considerations to improve usability (Berland et al. 2001; Eysenbach et al., 2002). Appropriately presented information can create a pleasant feeling and attract individuals' attention, while sloppy presentation can easily turns off their interest. In addition, online health information must be readable to lay people because there are no physicians beside the user to explain medical jargons.

**H5a:** Accessibility is positively associated with system quality.

**H5b:** Delay is negatively associated with system quality.

**H5c:** Navigability is positively associated with system quality.

**H5d:** Presentation is positively associated with system quality.

**H5e:** Readability is positively associated with system quality.

# 4 Method

## 4.1 Measurement Development

We developed the measures of the constructs based on the existing literature. If we found no existing measurement for a construct, we developed the items ourselves. We measured the physical disability level using the 10-item physical function component of the SF-36 survey (Ware & Sherbourne, 1992). SF-36 is a well-established instruments for measuring physical and mental health and has been widely used in clinical research and practice (Ware & Gandek, 1998). Its validity has long been established through clinical data (McHorney, Ware, & Raczek, 1993). In particular, research has often used the physical function component of SF-36 as a measure of physical disability, an approach that numerous studies have justified and validated (Davidson & Keating, 2002; Syddall, Martin, Harwood, Cooper, & Sayer, 2009; ten Klooster et al., 2013). Researchers recognize it as a simple and effective measure for physical disability (Syddall et al., 2009), and they have demonstrated its validity by comparing it with other established measures of physical disability (ten Klooster et al., 2013). Each item of the SF-36 physical function component evaluates a person’s limitation in performing a given physical activity. Following the SF-36 scoring guide (Ware, Kosinski, & Dewey, 2002), one obtains a physical function score by averaging the 10 item scores. The range of this score is 0 to 100, and higher scores represent better physical functions. We transformed this score to create a disability score by subtracting it from 100, so that 0 represents no physical disability at all and 100 represents the most severe physical disability.

We based the measures for information quality, completeness, accuracy, currency, accessibility, and delay on Wixom and Todd (2005). We based the readability and transparency items on Eysenbach et al. (2002). We derived the measures for navigation and presentation from Bart et al. (2005). We adapted the items for information use from Liang et al. (2011). We developed the measures of system quality, perceived benefit, and perceived risk ourselves based on theory and our research context. Although Wixom and Todd (2005) have developed a scale for system quality, that scale measures the overall quality of a system that has defined boundaries in organizational settings. In our research context, the “system” is not well defined and can be thought of as the Internet. Providing health information is only a small set of what the Internet offers. It is inappropriate to measure the general system quality of the Internet in this case. Therefore, we self-developed items to specifically measure the quality of the Internet in terms of how it affects users’ seeking of online health information. Following Lee (2009) and Pavlou (2003), we measured perceived benefit and perceived risk by identifying specific benefits and risks (or potential losses and costs) associated with online health information and assessed the respondents’ agreement that these benefits and risks could occur. Appendix A provides all of the measurement items.

To evaluate the content validity of the measures, we conducted a pretest. Two business professors, two nursing professors, and 30 undergraduate students in a major public university in the US reviewed the items and provided feedback. We made minor changes to some items to remove confusing words and expressions. Except for physical disability level, we evaluated all of the items with a seven-point Likert scale (1 = “strongly disagree” and 7 = “strongly agree”). Research has found that demographic characteristics such as age, gender, education level, income, and employment status may have a potential influence on individuals’ using the Internet for health information (Cohen & Adams, 2011; Fox & Duggan, 2013); therefore, we included these characteristics as control variables. In addition, we included residency location, Web experience, and e-health literacy as additional control variables because of their potential impact on individuals’ access to Internet services, Web-searching skills, and capability to evaluate health information. We adapted the measurement items for e-health literacy from Norman and Skinner (2006), which focus on individuals’ ability in evaluating and applying health information gained in electronic environments towards solving a health problem.

## 4.2 Data Collection

We conducted an online survey to collect data. The survey subjects included people who had physical disabilities and were at least 18 years’ old. We posted invitations in two general social networking websites including Facebook and MySpace and nine online forums and support groups for disabling conditions such as multiple sclerosis, ALS, Parkinson’s disease, and muscular dystrophy. The data collection lasted four months, during which we posted three invitations with the survey link onto each website to remind the respondents. We assured respondents that participation in the survey was voluntary, that we collected survey data anonymously, and that we would use the results only for research purposes. We used the physical disability scale as screening questions. We excluded respondents whose physical disability score was 0 (no physical disability at all) from this study. As a result, our respondents included both people with minor disabilities and people with severe disabilities.

A total of 243 respondents that had physical disabilities returned completed questionnaires. Their average age was 42.44 (SD = 18.04). The majority (73.7%) of them were male. More than half of them (61.7%) had college education. Most of them (79%) did not have a fulltime job. Their average annual income was US$41.40K (SD = US$40.13K). Most of them (72.4%) lived in urban areas. On average, they had 10.1 (SD = 4.20) years of Internet experience. Their average disability score is 55.72 (SD = 31.80). Compared with the Americans' average disability score of 15.8 (Ware et al. 2002), our respondents had a much higher physical disability rating.

# 5 Results

## 5.1 Measurement Evaluation

We used partial least square (PLS) for subsequent data analyses (Ringle, Wende, & Will, 2005). We used PLS based on the following considerations. First, as a second-generation component-based structural equation modeling technique, PLS can assess the measurement model and structural model simultaneously and is particularly suited for explaining complex relationships due to its advantages of avoiding two critical issues: inadmissible solutions and factor indeterminacy (Fornell & Bookstein, 1982). Second, different from covariance-based structural equation modeling (CB-SEM), PLS is robust with fewer statistical identification issues (Hair et al. 2011). Prior research has found that PLS and CB-SEM can provide very similar parameter estimations and that PLS has more power in maximizing variance explained (Gefen, Rigdon, & Straub, 2011; Hair, Ringle, & Sarstedt, 2011). Since we focus on explain variance in the online health information use behavior of people with physical disabilities, we believe PLS is appropriate for analyzing data in this study.

Before testing hypotheses, we evaluated the validity and reliability of the construct measures. Following Gefen et al. (2011), we tested the validity of the measures using two procedures. First, we calculated factor loadings and cross loadings for all the constructs. As Table 1 shows, the loading of each item on its substantive construct was over .70, which suggests sufficient convergent validity (Peng & Lai, 2012). In addition, each item's factor loading was much higher than its cross-loadings on other constructs, which confirms the sufficiency of discriminant validity (Hair, Anderson, Tatham, & Black, 1998). Second, as Table 2 shows, the square root of each construct's average variance extracted (AVE) was much greater than the construct's correlations with all other constructs, which suggests sufficient discriminant validity. We examined the reliability of the measurements by computing composite reliability. As Table 2 shows, all reliability scores exceeded Nunnally's (1978) recommended cut-off of .70.

**Table 1. Loadings and Cross Loadings**

| | accu | com | curr | trans | IQ | acce | delay | navig | pres | read | SQ | PR | PB | use |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| accu1 | 0.96 | 0.39 | 0.58 | 0.42 | 0.59 | 0.41 | 0.38 | 0.47 | 0.42 | 0.28 | 0.39 | -0.32 | 0.35 | 0.30 |
| accu2 | 0.95 | 0.47 | 0.60 | 0.35 | 0.55 | 0.35 | 0.27 | 0.39 | 0.35 | 0.29 | 0.36 | -0.36 | 0.30 | 0.33 |
| com1 | 0.35 | 0.91 | 0.39 | 0.38 | 0.46 | 0.34 | 0.21 | 0.24 | 0.21 | 0.08 | 0.35 | -0.30 | 0.20 | 0.27 |
| com2 | 0.46 | 0.90 | 0.46 | 0.35 | 0.46 | 0.41 | 0.28 | 0.35 | 0.20 | 0.11 | 0.40 | -0.24 | 0.28 | 0.31 |
| com3 | 0.37 | 0.82 | 0.40 | 0.35 | 0.38 | 0.15 | 0.14 | 0.23 | 0.17 | 0.01 | 0.22 | -0.34 | 0.16 | 0.40 |
| curr1 | 0.54 | 0.49 | 0.90 | 0.44 | 0.43 | 0.46 | 0.36 | 0.46 | 0.36 | 0.31 | 0.37 | -0.27 | 0.30 | 0.29 |
| curr2 | 0.59 | 0.50 | 0.94 | 0.44 | 0.43 | 0.43 | 0.33 | 0.43 | 0.39 | 0.24 | 0.38 | -0.27 | 0.32 | 0.23 |
| curr3 | 0.53 | 0.27 | 0.86 | 0.32 | 0.39 | 0.43 | 0.30 | 0.44 | 0.39 | 0.34 | 0.32 | -0.32 | 0.27 | 0.19 |
| trans1 | 0.47 | 0.40 | 0.50 | 0.76 | 0.57 | 0.49 | 0.36 | 0.41 | 0.42 | 0.39 | 0.43 | -0.36 | 0.18 | 0.12 |
| trans2 | 0.32 | 0.28 | 0.33 | 0.82 | 0.45 | 0.22 | 0.28 | 0.24 | 0.31 | 0.13 | 0.11 | -0.20 | 0.32 | 0.27 |
| trans3 | 0.18 | 0.29 | 0.28 | 0.81 | 0.35 | 0.28 | 0.22 | 0.24 | 0.33 | 0.12 | 0.20 | -0.15 | 0.16 | 0.14 |
| trans4 | 0.30 | 0.32 | 0.28 | 0.83 | 0.48 | 0.27 | 0.34 | 0.24 | 0.23 | 0.05 | 0.19 | -0.18 | 0.21 | 0.24 |
| trans5 | 0.26 | 0.34 | 0.34 | 0.79 | 0.40 | 0.33 | 0.33 | 0.33 | 0.35 | 0.14 | 0.25 | -0.20 | 0.26 | 0.26 |
| IQ1 | 0.56 | 0.47 | 0.44 | 0.57 | 0.97 | 0.51 | 0.46 | 0.44 | 0.41 | 0.31 | 0.49 | -0.24 | 0.40 | 0.33 |

**Table 1. Loadings and Cross Loadings**

| | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| IQ2 | 0.61 | 0.49 | 0.47 | 0.56 | 0.97 | 0.49 | 0.36 | 0.41 | 0.43 | 0.27 | 0.51 | -0.24 | 0.49 | 0.37 |
| acce1 | 0.36 | 0.31 | 0.44 | 0.35 | 0.50 | 0.86 | 0.48 | 0.39 | 0.39 | 0.39 | 0.54 | -0.09 | 0.42 | 0.21 |
| acce2 | 0.39 | 0.35 | 0.47 | 0.42 | 0.55 | 0.95 | 0.53 | 0.53 | 0.47 | 0.40 | 0.66 | -0.19 | 0.38 | 0.23 |
| acce3 | 0.28 | 0.25 | 0.36 | 0.29 | 0.29 | 0.81 | 0.34 | 0.43 | 0.46 | 0.25 | 0.52 | -0.08 | 0.15 | 0.11 |
| delay1 | 0.24 | 0.18 | 0.35 | 0.18 | 0.26 | 0.38 | 0.76 | 0.41 | 0.27 | 0.30 | 0.22 | -0.14 | 0.15 | 0.16 |
| delay2 | 0.20 | 0.11 | 0.22 | 0.22 | 0.18 | 0.28 | 0.74 | 0.33 | 0.25 | 0.09 | 0.12 | -0.03 | 0.11 | 0.16 |
| delay3 | 0.34 | 0.24 | 0.30 | 0.45 | 0.46 | 0.51 | 0.90 | 0.38 | 0.31 | 0.13 | 0.36 | -0.14 | 0.27 | 0.17 |
| navig1 | 0.36 | 0.34 | 0.47 | 0.34 | 0.40 | 0.51 | 0.40 | 0.91 | 0.45 | 0.45 | 0.53 | -0.21 | 0.24 | 0.33 |
| navig2 | 0.41 | 0.30 | 0.45 | 0.36 | 0.42 | 0.45 | 0.42 | 0.89 | 0.55 | 0.36 | 0.50 | -0.21 | 0.18 | 0.24 |
| navig3 | 0.40 | 0.14 | 0.35 | 0.25 | 0.30 | 0.36 | 0.36 | 0.77 | 0.25 | 0.60 | 0.43 | -0.24 | 0.22 | 0.19 |
| pres1 | 0.25 | 0.19 | 0.32 | 0.31 | 0.29 | 0.38 | 0.24 | 0.39 | 0.84 | 0.19 | 0.28 | -0.11 | 0.12 | 0.10 |
| pres2 | 0.42 | 0.21 | 0.42 | 0.42 | 0.44 | 0.51 | 0.33 | 0.45 | 0.92 | 0.28 | 0.44 | -0.19 | 0.29 | 0.15 |
| pres3 | 0.32 | 0.15 | 0.30 | 0.26 | 0.31 | 0.34 | 0.30 | 0.40 | 0.74 | 0.12 | 0.26 | -0.18 | 0.14 | 0.29 |
| read1 | 0.20 | -0.05 | 0.16 | 0.09 | 0.14 | 0.21 | 0.09 | 0.35 | 0.16 | 0.81 | 0.33 | -0.20 | 0.14 | 0.02 |
| read2 | 0.36 | 0.15 | 0.41 | 0.28 | 0.31 | 0.43 | 0.27 | 0.51 | 0.27 | 0.81 | 0.52 | -0.29 | 0.23 | 0.16 |
| read3 | 0.17 | 0.06 | 0.22 | 0.13 | 0.18 | 0.22 | 0.16 | 0.39 | 0.14 | 0.77 | 0.31 | -0.21 | 0.11 | 0.03 |
| read4 | 0.19 | 0.06 | 0.24 | 0.18 | 0.29 | 0.37 | 0.14 | 0.46 | 0.21 | 0.89 | 0.49 | -0.20 | 0.14 | 0.02 |
| SQ1 | 0.44 | 0.37 | 0.45 | 0.36 | 0.52 | 0.61 | 0.38 | 0.55 | 0.53 | 0.41 | 0.83 | -0.23 | 0.54 | 0.35 |
| SQ2 | 0.25 | 0.22 | 0.25 | 0.16 | 0.34 | 0.44 | 0.17 | 0.40 | 0.23 | 0.42 | 0.80 | -0.27 | 0.19 | -0.02 |
| SQ3 | 0.26 | 0.31 | 0.25 | 0.21 | 0.39 | 0.58 | 0.24 | 0.45 | 0.20 | 0.49 | 0.87 | -0.19 | 0.32 | 0.07 |
| PR1 | -0.33 | -0.35 | -0.23 | -0.24 | -0.25 | -0.04 | -0.05 | -0.18 | -0.10 | -0.08 | -0.16 | 0.86 | -0.05 | -0.27 |
| PR2 | -0.28 | -0.19 | -0.34 | -0.25 | -0.09 | -0.23 | -0.16 | -0.29 | -0.26 | -0.27 | -0.27 | 0.78 | -0.02 | -0.06 |
| PR3 | -0.26 | -0.16 | -0.27 | -0.20 | -0.17 | -0.16 | -0.14 | -0.13 | -0.22 | -0.24 | -0.25 | 0.79 | 0.00 | 0.01 |
| PR4 | -0.23 | -0.23 | -0.25 | -0.21 | -0.17 | -0.16 | -0.18 | -0.24 | -0.18 | -0.43 | -0.27 | 0.74 | -0.03 | -0.14 |
| PB1 | 0.30 | 0.19 | 0.36 | 0.23 | 0.33 | 0.34 | 0.19 | 0.25 | 0.17 | 0.30 | 0.48 | -0.06 | 0.86 | 0.42 |
| PB2 | 0.24 | 0.19 | 0.25 | 0.31 | 0.36 | 0.33 | 0.22 | 0.14 | 0.17 | 0.16 | 0.36 | 0.03 | 0.90 | 0.46 |
| PB3 | 0.19 | 0.14 | 0.10 | 0.14 | 0.29 | 0.13 | 0.15 | 0.14 | 0.17 | -0.06 | 0.16 | 0.09 | 0.73 | 0.55 |
| PB4 | 0.39 | 0.27 | 0.36 | 0.25 | 0.53 | 0.41 | 0.26 | 0.27 | 0.27 | 0.23 | 0.46 | -0.18 | 0.83 | 0.40 |
| use1 | 0.39 | 0.32 | 0.25 | 0.29 | 0.43 | 0.21 | 0.19 | 0.32 | 0.33 | 0.20 | 0.18 | -0.17 | 0.48 | 0.76 |
| use2 | 0.18 | 0.34 | 0.14 | 0.19 | 0.23 | 0.09 | 0.17 | 0.18 | 0.06 | -0.06 | 0.11 | -0.15 | 0.37 | 0.85 |
| use3 | 0.22 | 0.22 | 0.24 | 0.13 | 0.21 | 0.20 | 0.12 | 0.21 | 0.09 | 0.05 | 0.16 | -0.16 | 0.45 | 0.78 |

Note: accu = accuracy; comp = completeness; curr = currency; trans = transparency; IQ = information quality; acce = accessibility; navig = navigability; pres = presentation; read = readability; SQ = system quality; PR = perceived risk; PB = perceived benefit; use = information use

Table 2. Correlation Matrix

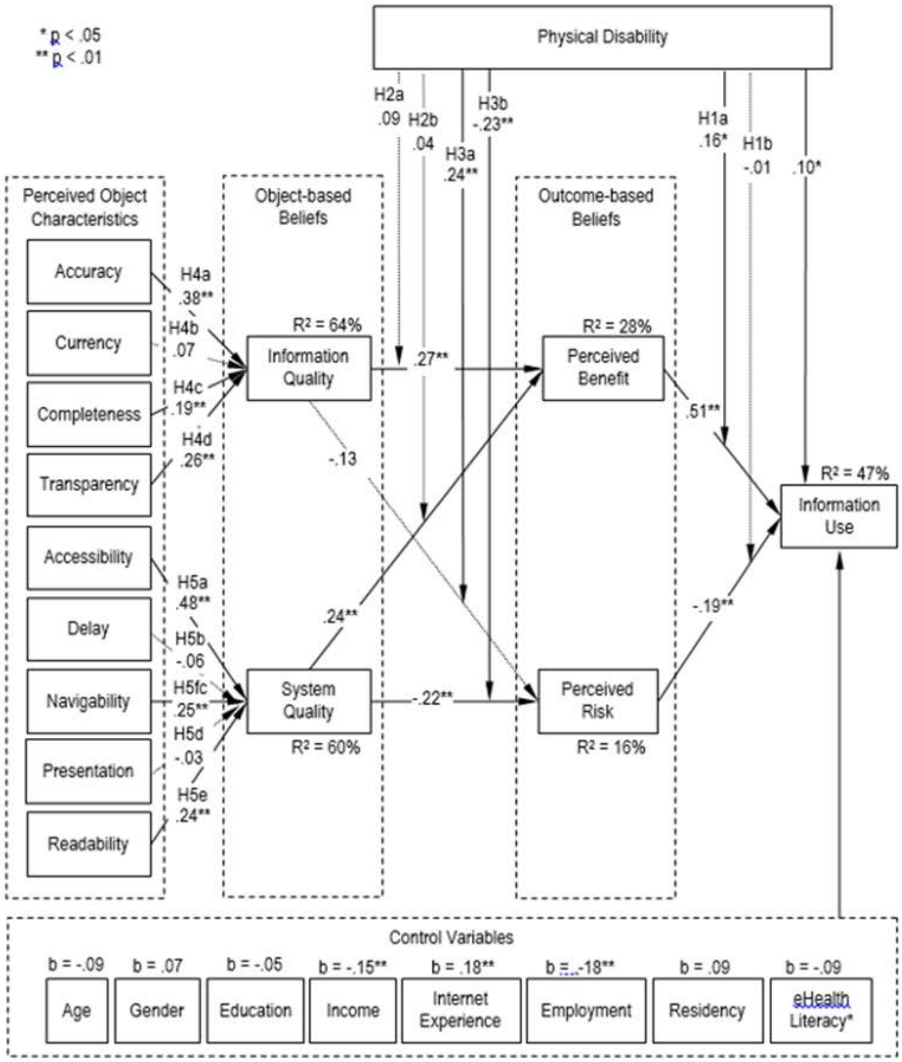
| | AVE | R | age | Sex | disab | edu | Inc | job | resid | exp | ehl | accu | comp | curr | trans | IQ | acce | delay | navig | pres | read | SQ | PR | PB | use |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| age | 1.00 | 1.00 | 1.00 | | | | | | | | | | | | | | | | | | | | | | |
| sex | 1.00 | 1.00 | .11 | 1.00 | | | | | | | | | | | | | | | | | | | | | |
| disab | 1.00 | 1.00 | .18 | .09 | 1.00 | | | | | | | | | | | | | | | | | | | | |
| edu | 1.00 | 1.00 | .23 | -.08 | - .15 | 1.00 | | | | | | | | | | | | | | | | | | | |
| inc | 1.00 | 1.00 | .31 | .10 | -.10 | .23 | 1.00 | | | | | | | | | | | | | | | | | | |
| job | 1.00 | 1.00 | .07 | .10 | .18 | -.11 | -.10 | 1.00 | | | | | | | | | | | | | | | | | |
| resid | 1.00 | 1.00 | -.01 | -.04 | -.01 | .16 | .03 | .14 | 1.00 | | | | | | | | | | | | | | | | |
| exp | 1.00 | 1.00 | .09 | -.004 | -.06 | .11 | -.05 | -.07 | -.03 | 1.00 | | | | | | | | | | | | | | | |
| ehl | .88 | .95 | -.09 | -.17 | .06 | .40 | .12 | -.20 | -.24 | .10 | .94 | | | | | | | | | | | | | | |
| accu | .91 | .95 | .03 | .06 | .10 | -.06 | .11 | -.08 | -.07 | -.20 | .51 | .95 | | | | | | | | | | | | | |
| comp | .77 | .91 | .08 | .08 | .12 | -.10 | -.03 | .02 | -.03 | -.10 | .30 | .45 | .88 | | | | | | | | | | | | |
| curr | .81 | .93 | -.02 | -.03 | .08 | .04 | -.01 | -.15 | -.11 | -.17 | .49 | .62 | .47 | .90 | | | | | | | | | | | |
| trans | .64 | .90 | .02 | -.08 | .23 | -.19 | -.16 | -.04 | -.14 | .07 | .45 | .40 | .41 | .45 | .80 | | | | | | | | | | |
| IQ | .95 | .97 | .09 | .04 | .16 | -.15 | .07 | -.02 | -.05 | -.07 | .54 | .60 | .49 | .47 | .58 | .97 | | | | | | | | | |
| acce | .76 | .91 | -.04 | -.15 | .17 | -.08 | -.04 | -.06 | -.12 | -.04 | .57 | .40 | .35 | .49 | .41 | .52 | .87 | | | | | | | | |
| delay | .64 | .84 | .01 | -.11 | .16 | -.10 | -.17 | -.08 | -.08 | -.05 | .39 | .34 | .24 | .36 | .39 | .42 | .52 | .80 | | | | | | | |
| navig | .74 | .89 | -.10 | -.13 | -.07 | .03 | -.05 | -.13 | .02 | .03 | .43 | .45 | .31 | .50 | .37 | .44 | .52 | .46 | .86 | | | | | | |
| pres | .70 | .87 | -.04 | -.10 | .03 | -.04 | .03 | -.02 | .01 | .00 | .37 | .40 | .22 | .42 | .41 | .43 | .50 | .35 | .49 | .83 | | | | | |
| read | .67 | .89 | .01 | -.01 | -.03 | .23 | .17 | -.04 | -.03 | .05 | .40 | .29 | .08 | .33 | .22 | .30 | .40 | .21 | .54 | .25 | .82 | | | | |
| SQ | .70 | .79 | .07 | -.05 | .05 | .04 | .004 | -.02 | -.004 | -.07 | .41 | .39 | .37 | .40 | .31 | .51 | .66 | .33 | .57 | .41 | .53 | .83 | | | |
| PR | .63 | .87 | -.06 | .01 | -.08 | .11 | -.03 | -.02 | .01 | .07 | -.19 | -.36 | -.33 | -.32 | -.28 | -.24 | -.14 | -.14 | -.25 | -.20 | -.28 | -.27 | .79 | | |
| PB | .69 | .90 | .10 | .05 | .06 | -.05 | .04 | -.09 | -.13 | .03 | .33 | .34 | .24 | .33 | .28 | .46 | .37 | .25 | .25 | .24 | .20 | .45 | -.04 | .83 | |
| use | .63 | .84 | -.08 | .12 | .03 | -.09 | -.12 | -.11 | .03 | .14 | .16 | .33 | .37 | .26 | .25 | .36 | .21 | .20 | .30 | .20 | .08 | .19 | -.20 | .55 | .80 |

Note: AVE = average variance explained; R = composite reliability; disab = disability level; sex (male = 1, female = 2); edu = education level; inc = annual income; job (fulltime = 1, otherwise = 2); resid = residence location (rural = 1, urban = 2); exp = Internet experience; ehl = eHealth literacy; accu = accuracy; comp = completeness; curr = currency; trans = transparency; IQ = information quality; acce = accessibility; navig = navigability; pres = presentation; read = readability; SQ = system quality; PR = perceived risk; PB = perceived benefit; use = information use; Square roots of AVE are shown in bold on diagonal.

Since we measured all of the constructs with respondents' self-reports, common method variance (CMV) could be a concern (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003; Podsakoff & Organ, 1986). Thus, we conducted two tests to evaluate CMV. First, we carried out the Harmon's one factor test by following Podsakoff et al. (2003). We entered the items of the theoretical constructs into a principal component analysis. The first factor of the unrotated solution explained only 24.24 percent of the total variance, which shows no indication of the existence of CMV. Second, we employed the correlational marker variable technique to assess CMV. Following Lindell and Whitney (2001), we selected the second smallest positive correlation amongst measurement items (r = .004) as a conservative estimate of CMV. We adjusted all of the between-item correlations by partialling out the CMV estimate. Results revealed that the correlations only changed slightly in magnitude and remained unchanged in significance, which suggests that CMV was unlikely a concern.

## 5.2 Hypothesis Testing

Figure 2 shows the model testing results. [The model] explained a total of 47 percent variance in information use. Most of the main effects were significant. Specifically, perceived benefit ($\beta = .51$, $p < .01$) increased and perceived risk ($\beta = -.19$, $p < .01$) reduced information use. Information quality ($\beta = .27$, $p < .01$) and system quality ($\beta = .24$, $p < .01$) were positively associated with perceived benefit and jointly explained 28 percent of its variance. In contrast, information quality ($\beta = -.13$, $p > .05$) and system quality ($\beta = -.22$, $p < .01$) were negatively associated with perceived risk and jointly explained 16 percent of its variance. However, the effect of information quality on perceived risk was not significant. Accuracy ($\beta = .38$, $p < .01$), completeness ($\beta = .19$, $p < .01$), and transparency ($\beta = .30$, $p < .01$) were positively associated with information quality and explained 64 percent of its variance, which supports H4a, H4c, and H4d. Currency did not significantly affect information quality ($\beta = .09$, $p < .01$), which does not support H4b. Accessibility ($\beta = .48$, $p < .01$), navigability ($\beta = .25$, $p < .01$), and readability ($\beta = .24$, $p < .01$) were positively associated with system quality and explained 60 percent of its variance, which supports H5a, H5c, and H5e. Since delay (β = -.06, p > .05) and presentation (β = -.03, p > .05) were not significantly related to system quality, the results do not support H5b and H5d.



Note: * ealth literacy's effect was also controlled on information quality (β = .13, p <.01), perceived benefit (β = .06, p > .05), and perceived risk (β = .01, p > .05).

**Figure 2. PLS Results of Model Testing**

We adopted the product indicator approach to create interaction terms that represent the moderation effects (Henseler & Chin, 2010). For each moderation effect, we created a latent interaction term. We computed a set of products by calculating all possible pairwise products of the independent latent variable's indicators and the latent moderator moderator's indicators. To reduce multicollinearity, we centered the indicators before multiplication (Chin, Marcolin, & Newsted, 2003). These product indicators became the latent interaction term's indicators. Because PLS does not rely on distribution assumptions, the latent independent variable and moderator variable do not need to be normally distributed to use the product indicator approach (Henseler & Chin, 2010).

We found that physical disability positively moderated the relationship between information quality and perceived risk (β = .24, $f2$ = .043, p < .01) and positively moderated the relationship between perceived benefit and information use (β = .15, $f2$ = .038, p < .01), which supports H3a and H1a. We also found that physical disability negatively moderated the relationship between system quality and perceived risk (β = -.23, $f2$ = .039, p < .01). The direction of this moderation was opposite to what we hypothesized, which does not support H3b. Each of these three moderation effects had a small effect size (Cohen, 1988). The moderation effect of disability on the relationships between system quality and perceived benefit (β = .09, p > .05), information quality and perceived benefit (β = .05, p > .05), and perceived risk and information use (β = -.002, p > .05) were not significant, which fails to support H1b, H2a, and H2b.

In addition, following Cohen, Cohen, West, and Aiken (2003), we plotted simple slopes to visually illustrate the moderation effects. A positive moderation of a negative relationship means that the relationship coefficient becomes greater but its absolute magnitude becomes smaller as the moderator increases (i.e., it is less negative when the moderator is at a higher level). As Figure 3 shows, physical disability positively moderated (or weakened) the negative relationship between information quality and perceived risk: at the low disability level, information quality strongly reduced perceived risk, but, at the high disability level, this relationship became slightly insignificantly positive. On the contrary, a negative moderation of a negative relationship means that the relationship coefficient becomes smaller but its magnitude becomes greater as the moderator increases (i.e., it is more negative when the moderator is at a higher level). Figure 4 reveals that physical disability negatively moderated (or strengthened) the negative relationship between system quality and perceived risk: at the low disability level, system quality had no significant effect on perceived risk, but, at the high disability level, this relationship was strongly negative. Finally, Figure 5 shows that physical disability strengthened the positive relationship between perceived benefit and health information use: at the low disability level, perceived benefit had a strong effect on information use, and this effect grew even stronger at the high disability level.

Finally, we tested the possible influences of control variables. Three of the eight control variables had a significant effect on information use. Income was negatively related to information use, which suggests people who have higher incomes are less likely to use online health information than those who have a lower income. This finding is consistent with a Pew Internet survey that found that people with higher income are more likely to search online health information but less likely to follow up with the information (Fox & Duggan, 2013). Another study has found that high-income individuals search for online health information less frequently than low-income individuals (Goldner, 2006). We found that Internet experience was positively related to information use, which suggests that experienced Internet users are more likely to use online health information than novice Internet users. A plausible explanation for this finding is that individuals with more Internet experiences have better skills to find the exact health information they need (Fox & Duggan, 2013). In addition, employment status (1 = no; 2 = yes) had a positive effect on online health information use. This finding is consistent with the National Health Interview Survey that shows that employed adults are more likely than unemployed adults to use the Internet for health information (Cohen & Adams, 2011). Due to the importance of e-health literacy, we tested its effects on four constructs in our model: online health information use, perceived benefit, perceived risk, and information quality. We found only the effect on information quality to be significant (β = .13, p < .05), which suggests that individuals tend to perceive higher quality of online health information as their e-health literacy increases possibly because they are better at seeking, interpreting, appraising, and applying the information (Norman & Skinner, 2006).

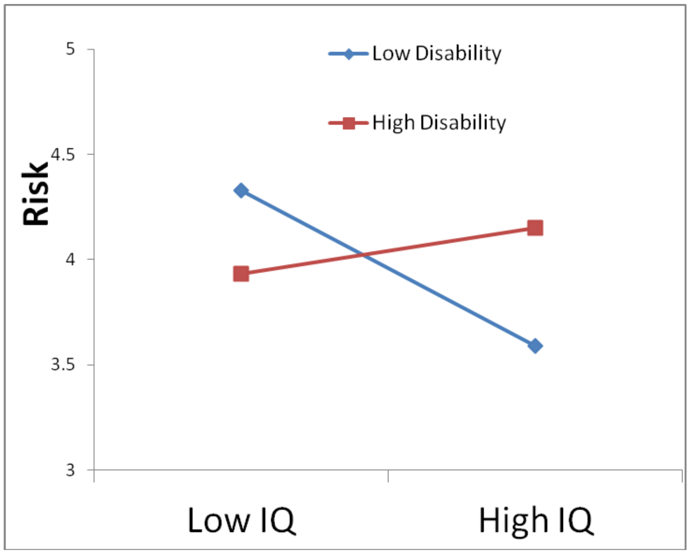


**Figure 3. Physical Disability Weakens the Negative Relationship Between Information Quality and Perceived Risk**

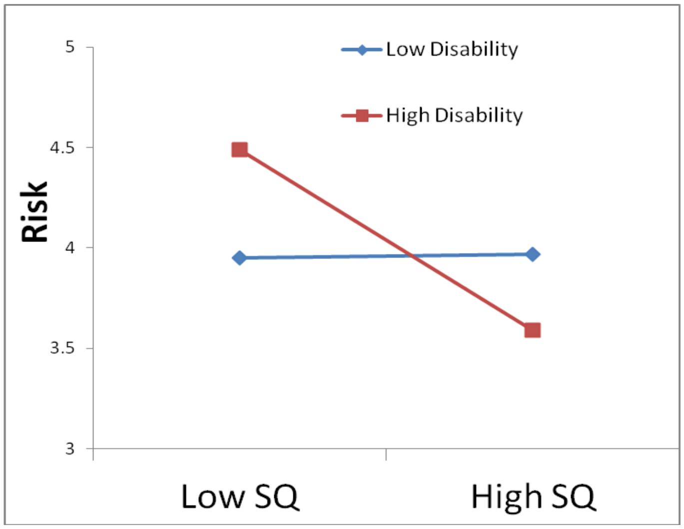


**Figure 4. Physical Disability Strengthens the Negative Relationship Between System Quality and Perceived Risk**

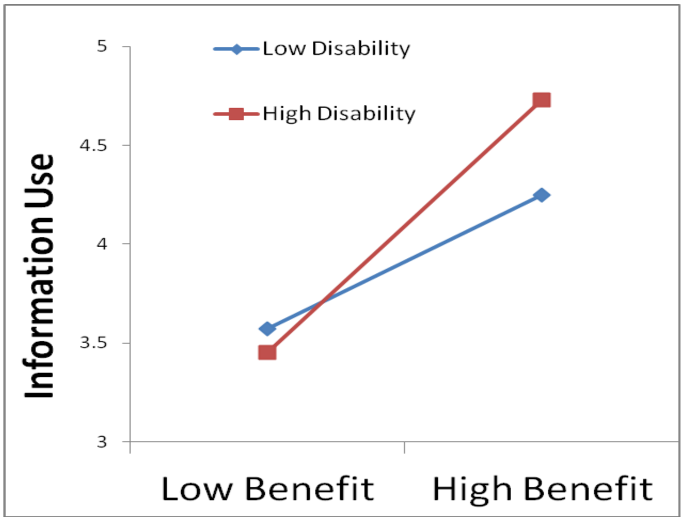


**Figure 5. Physical Disability Strengthens the Positive Relationship Between Perceived Benefits and Online Health Information Use**

# 6 Discussion

## 6.1 Implications for Research

This research makes four contributions to IS research. First, we address the issue of online health information use by people with physical disabilities. The main stream IS research has largely neglected this minority group, and few studies have focused on their interaction with IT. Yet, due to their unique characteristics, people with disabilities have special requirements and concerns about IT, which present unique challenges to IS designers and researchers (Lafky & Horan, 2011; Tulu & Horan, 2009). Our study focuses on the online health information use behavior of people with disabilities, which fills a void in the IS literature.

Second, we integrate rational choice theory and the IS success model to develop a theoretical framework that provides a holistic view of the shaping of online health information use behavior. The findings reveal that one can treat people's online health information use behavior as an approximately rational process. Rational beliefs such as perceived benefit and risk explain a large percentage of variance in information use. More importantly, this research shows how object-based beliefs can influence rational beliefs based on individuals' perceptions of information characteristics and system characteristics. Our work adapts rational choice theory into the context of online health information use by delineating specific antecedents of rational beliefs, which offers an in-depth understanding of online health information use. The two layers of antecedents reveal possible theoretical mechanisms through which rational beliefs are generated and add great richness to rational choice theory. In the meantime, we note that medicine is a specialized knowledge domain and average people have limited medical expertise to evaluate health information (Sharma, 1997). Hence, the online health information use behavior of people with physical disabilities is based on decisions that are boundedly rational (Simon, 1976). The so-called rational choice serves to be satisficing rather than to be objectively optimal (Simon, 1956).

Third, in this research, we investigate the use of online health information by people with physical disabilities. Information use is an important behavior in the healthcare context because information cannot have any impacts on health unless users consume it. IS researchers have noted the importance of this behavior but have only empirically studied users' intention to use online health information (e.g., Song & Zahedi, 2007). This paper fills the gap in the literature by delineating the key factors that influence the online health information use behavior of people with physical disabilities. Additionally, we identify a set of information characteristics and system characteristics that can influence information use through the mediation of object-based and outcome-based beliefs. Others can use these findings to guide research on website design for people with physical disabilities.

Finally, the moderating role of disability provides contextualized theoretical insights about how people with disabilities make judgments and decisions differently. We found that disability moderated the effects of information quality and system quality on perceived risk but did not moderate their effects on perceived benefit of online health information use. This finding suggests that people's sensitivity to risks changes with the level of physical disability, whereas their sensitivity to benefits is the same across disability levels. It further suggests that physical disability can influence how people develop risk perceptions by weighing antecedents differently. Not only did system quality ($b = -.22$) have a stronger direct effect than information quality ($b = -.13$) on perceived risk, but its effect became even stronger at a higher disability level, while the effect of information quality declined when disability increased. Regarding the use behavior of online health information, perceived benefit ($b =.49$) had a stronger influence than perceived risk ($b = -.18$). As disability increased, perceived benefit had a stronger effect on information use, whereas the effect of perceived risk remained unchanged at different levels of physical disability. The disability literature has long found perceived risk to be a salient factor in patients' health decision making and behavior change (Knox, Douglas, & Bigby, 2013; Plontikoff & Trihn, 2010). Prior research has also found that people with physical disabilities are more sensitive to risk perceptions when they are objectively at risk (Bassett & Ginis, 2011). However, the findings about the role of perceived risk are inconsistent in the disability literature. For example, some studies have shown that perceived risk is not a significant antecedent of patients' adoption of healthy behaviors (Perrier, Shirazipour, & Latimer-Cheung, 2015). It is possible that the unique characteristics of people with disabilities contribute to these inconsistencies. Yet, little research has taken a contingency approach to study how perceived risk is influenced by or influences other outcomes with the level of disability as a moderator. The interesting findings of this study and our theory-based explanations could open new avenues for research into behaviors of people with disabilities.

Since the negative moderation effect of physical disability on the relationship between system quality and perceived risk was significant but opposite to our hypothesis, we provide a plausible explanation to account for this surprising finding. Please note that the following explanation is largely speculative and propose it to stimulate future research interests in this area. When individuals' physical disability is severe, they need more user-friendly system features to accommodate their special needs. Based on the W3C's Web Accessibility initiative (W3C, 2013a), websites should address visual, motor, auditory, and seizure issues so as to be more accessible to people with disabilities. For example, people with Parkinson's disease would like the system to be easier to navigate through, and, if their hands are too shaky to maneuver the cursor, they would probably like voice commands. When system quality is high, people with physical disabilities are likely to find the health information they need with ease, which fosters a feeling of control (Bandura, 2001). With the perception of control, people with disabilities tend to experience positive emotions such as enjoyment, excitement, joy, and empowerment (Goetz, Frenzel, & Stoeger, & Hall, 2010; Pekrun, 2006). Prior research has shown that, when individuals make judgments and evaluations in positive moods, they are inclined to choose the less effortful approach that agrees with their mood because the more effortful approach would lead to negative emotions and undermine their positive mood (Garbarino & Edell, 1997). When assessing the risk of online health information use, using information quality is more effortful than using system quality because it requires specialized knowledge to evaluate the content of health information, whereas it only requires common sense to evaluate system quality. Therefore, under the influence of positive emotions, people with physical disabilities would rely more on system quality to assess the risk of online health information use. As people's disability gets more severe, their expectation of being able to interact with the Internet is lower; thus, once they find out that they can accomplish the task just like normal people, their positive emotions tend to be more intense. As a result, they will rely on system quality more heavily and its mitigating effect on perceived risk will be stronger. While this explanation seems intuitive, future research needs to empirically validate the specific mechanism.

## 6.2 Implications for Practice

This research has implications for practice in both IS and healthcare. For IS practice, we found that both information quality and system quality factor into physically disabled people's perceptions of benefit and risk related to online information use and that they eventually influence their information use behavior. Hence, to help people with physical disabilities appropriately assess benefits versus risks, healthcare websites should enhance the design features related to information quality and system quality. First, the health information should be accurate, complete, up to date, and transparent. They should apply advanced content management tools to ensure information accuracy, completeness, and currency. Transparency is particularly important because it is the only feature that one does not need to evaluate with specialized medical knowledge. Healthcare websites can become more transparent by disclosing information such as sources (authors, research institutes, organizations, or companies), sponsorship (private or public), references (for readers to validate the information), and privacy policies (disclaimer and third-party certificates such as TRUSTe). While researchers have advocated these practices for e-commerce websites (Pavlou et al., 2007), they should be particularly emphasized for healthcare websites because the sheer importance of health-related consequences. Second, based on our findings, healthcare websites can establish high system quality for people with physical disabilities by improving accessibility and navigability of the website and readability of the information content. Among various technological characteristics, accessibility is the strongest predictor of system quality, which suggests the special need of people with disabilities. Web accessibility allows people with physical disabilities to interact with websites to access the content, which increases the social inclusion of these people. By making their websites accessible to people with physical disabilities, organizations can show a commitment to providing equal opportunities to all stakeholders and increase the impact of their outreach effort.

Our study's implications for healthcare practices mainly come from the moderating role of physical disability. The moderation effects of physical disability suggest that, for people with more severe disabilities, system quality more strongly reduces their risk perception of online health information use. As Figures 3 and 4 illustrate, at the high disability level, information quality had no significant relationship with perceived risk whereas system quality had a strong negative effect on perceived risk. This tendency is dangerous because system quality can be deceiving. Although heuristic judgments based on system quality are instrumental to human decision making (Slovic et al., 2004), one can deliberately manipulate heuristics to mislead individuals' judgments. For example, cybercriminals can easily fabricate a fake website to mimic a legitimate company (Abbasi et al., 2012). Although every detail of the website can give people an impression of high system quality, one cannot trust the information provided on the fake website. Therefore, relying overly on system quality to judge risks of online health information use could make people with physical disabilities vulnerable to low-quality information. Public health education programs should raise awareness of this potential danger and teach people with disabilities alternative ways to assess risks. For example, strategies to detect fake websites and to evaluate information quality, especially transparency features such as sponsorship, source, references, and privacy certificates, should be emphasized to people with disabilities.

Moreover, physical disability also moderated the relationship between perceived benefit and information use, which suggests that perceived benefit more strongly determines the information use behavior of people with severe disabilities, which seems mindful. However, due to the unique nature of health information use, it could also be a pitfall. Because average people are not medical experts and, thus, lack sufficient knowledge to predict the outcome of using online health information, their perceptions of benefits are only boundedly rational and constrained by their personal experience and knowledge. Therefore, the perceptions of benefits are not clinically proven and could be exaggerated or simply be wishful thinking. Overusing online health information could expose people with disabilities to unnecessary harm. For example, a person who follows online health information to perform self-care could miss the best timing for treatment and result in heightened disability. Further, online health information could lead to escalation of concerns about common symptoms and, thus, cause unexpected anxiety (White & Horvitz, 2009). To guide people with physical disabilities to avoid being overly optimistic about online health information use, public health education programs should educate them about what benefits are realistic to expect from online health information, and the bottom line is that they should always consult a doctor if they have any doubts about the outcome.

### 6.3 Limitations and Future Research

This study has several limitations. First, our respondents self-reported their information use behavior, and we could not validate it with objective data. In addition, our model does not include the outcome of using online health information. We assume that online health information use represents a form of patient self-management and is considered adaptive. However, it is possible that inappropriate information use leads to unanticipated negative consequences. Future research should consider the final health outcome of online health information use and identify the appropriate use behaviors associated with positive health outcomes. Second, we recruited our sample via online forums and support groups. It is possible that the respondents had a more favorable attitude toward using online health information. Hence, one should interpret our findings with the generalizability limitedness in mind. Finally, in this study, we focus on a specific type of disability: physical disability. People with other types of disability such as cognitive or sensory disability are likely to face different challenges and have different characteristics that influence their use of online health information. One cannot readily apply our findings to people with those disabilities, and we need future research to understand how they use online health information.

## 7 Conclusion

This study investigates the online health information use behavior of people with physical disabilities. Our findings confirm that the two object-based beliefs (information quality and system quality) predict the two outcome-based beliefs (perceived benefit and perceived risk), which, in turn, determine information use. In addition, we found that the level of physical disability plays an intriguing moderator role: it weakens the negative relationship between information quality and perceived risk, strengthens the negative relationship between system quality and perceived risk, and strengthens the positive relationship between perceived benefit and information use. These findings suggest that people with physical disabilities are boundedly rational when using online health information and that they are inclined to be less rational as their disability gets more severe. We need future research to cast more light on the perceptions and behaviors of online health information use of people with disabilities.

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## Appendix A: Measures

Disability (Ware & Sherbourne, 1992)

The following items are about activities you might do during a typical day. Does your health now limit you in these activities? If so, how much? (1 = yes, limited a lot; 2 = yes, limited a little; 3 = no, not limited at all)

1. Vigorous activities, such as running, lifting heavy objects, participating in strenuous sports
2. Moderate activities, such as moving a table, pushing a vacuum cleaner, bowling, or playing golf
3. Lifting or carrying groceries
4. Climbing several flights of stairs
5. Climbing one flight of stairs
6. Bending, kneeling or stooping
7. Walking more than one mile
8. Walking several blocks
9. Walking one block
10. Bathing or dressing yourself

The following items are evaluated by a seven-point Likert scale (1 = strongly disagree; 2 = disagree; 3 = slightly disagree; 4 = neutral; 5 = slightly agree; 6 = agree; 7 = strongly agree)

Perceived benefit (self-developed)

1. Online health information would improve my capability of managing my conditions
2. Online health information would increase my knowledge of my personal health
3. Online health information would help me relieve stresses over my new symptoms or drug side effects
4. I would find online health information to be useful

Perceived risk (self-developed)

1. Online health information could be misleading
2. Online health information could harm my health
3. I could make wrong decision regarding my health based on poor quality online health information
4. I could be stressed out due to exaggerating online health information

System quality (self-developed)

1. My interaction with health websites is clear and understandable
2. Seeking online health information does not require a lot of my mental effort (reverse coded)
3. I find it easy to search the Internet for health information

Information quality (Wixom & Todd, 2005)

1. Overall, I would give online health information a high rating in terms of quality
2. In general, the Internet provides me with high-quality health information

Information use (Liang et al., 2011)

1. I follow the advice offered by online health information
2. Online health information heavily influences my personal health decisions
3. I use online health information to cope with my emotions such as fear, stress, and frustration

Completeness (Wixom & Todd, 2005)

1. The Internet provides me with a complete set of health information
2. The Internet produces comprehensive health information
3. The Internet provides me with all the health information I need

Accuracy (Wixom & Todd, 2005)

1. The internet provides correct health information
2. There are few errors in the health information I obtained from the Internet
3. Online health information is accurate

Currency (Wixom & Todd, 2005)

1. The Internet provides me with the most recent information
2. Health information from the Internet is mostly up to date
3. Most health information from the Internet is out of date

Transparency (Eysenbach et al., 2002)

1. Sources of health information provided by health websites are clear
2. Health websites discloses authorship of health articles
3. Health websites discloses date of creation or update for its health information
4. Health websites provides references to support its health information
5. Health websites discloses its ownership or sponsorship

Navigation (Bart et al., 2005)

1. It is easy to navigate through different web pages on the Internet
2. The overall layout of health websites is clear
3. I easily get lost when browsing health information on the Internet

Delay (Wixom & Todd, 2005)

1. It takes too long for health websites to respond to my search requests
2. Health websites returns answers to my searches quickly (reverse coded)
3. The speed by which information is displayed by health websites is fast enough (reverse coded)

Accessibility (Wixom & Todd, 2005)

1. The internet allows health information to be readily accessible to me
2. Online health information is easy to access
3. Online health information is accessible to me

Presentation (Bart et al., 2005)

1. Pictures and colors used in online health articles are attractive
2. Online health information is presented appropriately
3. Online health information is presented with appropriately sized fonts

Readability (Eysenbach et al., 2002)

1. The health information provided by the Internet contains too much medical jargon
2. It is easy to read health information from the Internet
3. The sentences in health articles on the Internet are too long
4. The health information from the Internet is difficult to understand

E-health Literacy (Norman & Skinner, 2006)

1. I have the skills I need to evaluate the health resources I find on the Internet
2. I can tell high quality from low quality health resources on the Internet
3. I feel confident in using information from the Internet to make health decisions

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