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Impact of Using Online Health Management Tools on Patient Perception of Healthcare Quality: A Multiple Chronic Conditions and Generational Perspective

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Abstract:

While access and adoption issues related to online health management tools (OHMT) have been studied in healthcare contexts, questions remain about whether and how their use impacts patients' perceptions of healthcare. Drawing on technology affordance and media synchronicity frameworks, we explore how the existence of multiple chronic conditions (MCC) and differences in usage pattern due to patient's generation impact these relationships. Utilizing HINTS data, this study provides empirical support for a positive relationship between utilization of electronic personal health records (e-PHRs) and healthcare quality perceptions, albeit with a caveat that patients with greater healthcare needs as well as millennial and younger generations do not seem to enjoy the same benefits from increased use of e-PHRs. Furthermore, asynchronous patient-provider electronic communication is yet to achieve positive perceptions of better healthcare quality for most users. This research bears implications for personalization and customization of OHMT to account for variations in patients' healthcare needs and usage patterns.

Keywords: Online Health Management Tools, E-Phr, E-Communication, Chronic Condition, Generation, Healthcare Quality.

1 Introduction

Prevalence of chronic diseases remains a significant burden on the United States (US) healthcare system (Bao, Bardhan, Singh, Meyer, & Kirksey, 2020). Preventing or minimizing their effects requires use of strategies and tools to empower chronic disease patients to manage their own health. The passage of the Health Information Technology for Economic and Clinical Health (HITECH) act in 2009 established the meaningful use incentive program and offered financial incentives to care providers in the US to encourage the use of health information technologies for improved patient engagement and care delivery (Lin, Lin, & Chen, 2019). Stage 2 of the meaningful use program in 2014 placed new requirements on healthcare organizations in terms of the use of technology to help advance the application of various online health management tools (OHMT) including patient portals, for increasing access to information and enhancing electronic patient–provider communication. A significant goal of OHMT is to deliver care aligned to patients' health needs and preferences (Mathai, McGill, & Toohey, 2020) by enabling them to organize their health records, monitor health conditions, share health-related information, make informed treatment decisions, and communicate with their providers. Two extensively used OHMT - Electronic Personal Health Records (e-PHRs) and asynchronous e-communication tools (email and text) have become an integral part of the persuasive strategy of using technology to engage chronic disease patients to take greater control of their health by empowering them with access to their own health records and communicate conveniently with their provider (Agrawal, Ndabu, Mulgund, & Sharman, 2021; Laugesen & Hassanein, 2017).

The expectation from the adoption and subsequent use of e-PHRs and asynchronous e-communication tools is that they enable better management of health and improve healthcare outcomes (Archer & Cocosila, 2014). Indeed, most chronic disease patients conceivably benefit from the use of OHMT (Bao et al., 2020) as they need regular access to health-related information and have to frequently correspond with their care providers (Laugesen & Hassanein, 2017). e-PHRs facilitate online access and management of personal health information (e.g., chronological record of blood sugar levels) and medication management (e.g., refilling medications online), while asynchronous communication via e-mails and/or texts enable efficient interaction with providers. Extant research has predominantly focused on adoption and access related to these OHMT (Abd-alrazaq, Bewick, Farragher, & Gardner, 2019; Cocosila & Archer, 2018; Laugesen & Hassanein, 2017; Lazard et al., 2016; Woods et al., 2017). However, research on whether and how perceptions of healthcare quality is impacted by use of e-PHRs and asynchronous e-communication tools, remains rather limited.

We argue that it is important to explore these relationships since the continued success of healthcare in most developed countries including the US is largely dependent on how patients' outlook towards and experience with the technologies for self-care and health management shape their perceptions of care quality (Alrubaiee & Alkaa'ida, 2011; Mohammed et al., 2016; Winkelman, 2005). Patients who can manage their health and interact with their provider effectively through various OHMT, will likely associate the use of such tools with an overall higher quality of healthcare. Thus, in order to improve delivery of healthcare, it is important to understand how patients recognize the role of widely used OHMT such as e-PHRs and asynchronous e-communication tools.

Prevalence of chronic diseases in the US is widespread and a significant percent of the population has not one, but multiple chronic conditions (MCC) ("About Chronic Diseases | CDC," n.d.). Individuals with MCC have a higher treatment burden due to multifaceted health problems that pose additional challenges compared to those with a single chronic illness (Zulman et al., 2014). Effective technology-enabled care management for people with MCCs is inherently difficult due to a multitude of factors – interactions among sets of clinical characteristics, medication adverse effects, as well as psycho-socioeconomic contexts (support systems, psychological and cognitive status, economic considerations to name a few) (Grembowski et al., 2014). Consequently, the use of e-PHRs and e-communication tools may considerably impact how patients with MCC view quality of care extended to them (Greenberg et al., 2017). Yet very few studies to date have examined the link between use of tools that facilitate self-management of MCC and individual perceptions of care quality.

In addition to the presence of MCC, individual's generation is cited as a significant factor in ascertaining benefits of OHMT for patient care (Lyles et al., 2013). Studies on generational effects on the access, adoption, and use of e-PHRs and asynchronous e-communication tools have found mixed results. While access to technology, declining cognitive ability, and lack of computer literacy are often cited as barriers for utilizing e-PHRs and e-communication systems for older patients (Walker, Hefner, Fareed, Huerta, & McAlearney, 2020), studies also cite higher levels of trust (Lyles et al., 2013) and a higher adoption potential for these patients (Archer, Fevrier-Thomas, Lokker, McKibbon, & Straus, 2011). This indicates the need for further investigating how generational differences may impact the perceptions of care quality when using these tools. Research (Venkatesh, Thong, & Xu, 2016) on patterns of a usage of technology amongst millennials (individuals born between 1980 and 1994) and subsequent generations have shown that these individuals inherently differ from older generations such as GenX, Baby Boomers, and the silent generations (Paige, Miller, Krieger, Stellefson, & Cheong, 2018). Millennials and younger generations are usually referred to as digital natives while individuals born before 1980, i.e. GenX and older are known as digital immigrants (Prensky, 2001). However, extant research has not explicitly studied how these digital native and immigrants may perceive care quality differently while using e-PHRs and asynchronous e-communication tools for self-care.

The purpose of this research is to explore how chronic disease patients perceive care quality when using OHMT, specifically e-PHRs and asynchronous communication tools, to manage their health and how such perceptions vary based on the presence of MCC and their generation. Specifically, we examine the following questions:

RQ1: How do e-PHR utilization and asynchronous e-communication with healthcare providers impact the perception of healthcare quality?

RQ2: How do greater need for technological support due to MCC and differences in technology usage patterns among different generations impact the perception of healthcare quality?

In this study we examine these questions by conducting an empirical study using the cross-sectional Health Information National Trends Survey (HINTS) data. We develop a conceptual model by leveraging the theoretical underpinnings provided in the technology affordances and media synchronicity frameworks and test the hypothesized relationships using moderated multiple regression. Adopting a two degrees of freedom research strategy (Berthon, Pitt, Ewing, & Carr, 2002), our work makes a theory/context extension by bringing together two existing theoretical frameworks to provide novel insights into the relationship between use of OHMT and perceived healthcare quality. In particular, the study provides a better understanding of OHMT usage and healthcare quality, especially for patients with MCC. Our results indicate that existing features of e-PHRs may be limited in their ability to reduce the burden of treatment for patients with MCC. Also highlighted is the stark difference in expectation between digital natives and digital immigrants about the role of OHMT as well its appropriateness as a medium for patient-provider interaction. Our results suggest that both the design of e-PHRs and communication strategies using asynchronous medium needs to evolve to cater to the millennials as they grow older.

2 Conceptual Framework

2.1 Perceived Healthcare Quality

Given that healthcare is a ‘service’ for patients (Alrubaiee & Alkaa’ida, 2011), it is important to understand the quality of the service delivery as perceived by the patients. While it is often challenging to define quality of service in healthcare (Eiriz & António Figueiredo, 2005), a conceptualization appropriate in the context of this study can be based on prior research (Xiang & Stanley, 2017) and may be defined as the extent of an individual’s belief that they are receiving the best possible care from their healthcare providers. While most patients lack the knowledge and skill to judge either the technical competence of their healthcare provider such as clinical and operating skills or the quality of the clinical outcomes (Eiriz & António Figueiredo, 2005), research has suggested that perceptions regarding healthcare quality depend on the availability of information in managing personal health, the care extended by the provider, and the explanations of illness and treatment (Naidu, 2009). Key objectives of various OHMT including e-PHRs, and e-communication systems has thus been to create an efficient and convenient method for patient access to health information, enable patients to manage their health information, and enhance interpersonal care by facilitating regular and commensurate patient-provider interaction (Bao et al., 2020). Patients may particularly value online reordering of prescriptions, online access to laboratory results, information about their specific health conditions, disease management plans, trend charts, medication lists, and communication with their care provider. Further, provider’s well-articulated communication with the patient regarding diagnosis, treatment, and type of care alleviates patient uncertainty about what to expect (Naidu, 2009). Such communications likely lead to higher patient satisfaction. In all these respects, that is, enhancing access to health information as well as enlightening the individual about their health condition and treatment, the role of both e-PHRs and e-communication tools is significant and is linked to how patients perceive the quality of healthcare (Atasoy, Greenwood, & McCullough, 2019; Wagner et al., 2012). While both OHMT are currently recognized as promising means to support greater patient satisfaction (Irizarry, DeVito Dabbs, & Curran, 2015), empirical research on how use of e-PHRs and e-communication tools impact healthcare quality perceptions remain scarce (Atasoy et al., 2019). In the following sections, we discuss the relevant literature leading to our empirical model to explore these relationships.

2.2 e-PHR Utilization and Perceived Healthcare Quality

A significant goal of healthcare as a service is to improve quality of life and develop standards of care aligned to patients' preferences. To achieve these objectives, it is essential to assess healthcare's quality as perceived by its consumers. Patient perceptions relevant to the quality of healthcare bear wide-ranging implications for overall efficacy of care delivery systems (Xiang & Stanley, 2017). Portals for electronic personal health records (e-PHRs) are consumer-oriented Internet-based tools designed to enable patients to access, monitor, and share their health information for improved care delivery (Irizarry et al., 2015). The use of e-PHRs has gathered growing interest as a method for improving the experience of care for chronic disease patients (Archer & Cocosila, 2014; Okpala, 2018) as they offer the potential for enhancing active involvement of individuals in managing their own health. Patients can schedule appointments, refill medication, get health-related information (Lyles et al., 2013; Otte-Trojel, de Bont, Rundall, & van de Klundert, 2014), as well as obtain relevant disease-specific information and decision support (Otte-Trojel et al., 2014) at their convenience, enabling them to become 'owners' of their health and well-being. It has been suggested that use of e-PHRs is associated with improvements in quality of care (Ancker et al., 2015). This study examined use of certain EHR functions (such as electronic reminders) by physicians and established the link between usage and improvement in care quality including better adherence to clinical guidelines, fewer medication errors, and improved chronic disease management. Alturkistani et al. (2020) reported improved glycemic control outcomes for patients with diabetes that used portals connected to electronic health records. while mobile-accessible e-PHRs resulted in improved self-management behaviors among patients with chronic conditions (Graetz, Huang, Brand, Hsu, & Reed, 2019; Seo et al., 2020). Use of e-PHRs was also linked to improved patient safety (Subbe, Tellier, & Barach, 2021). However, to the best of our knowledge, studies related to e-PHR use and how that impacts patient perception of care quality are non-existent. The importance of understanding patient expectations of healthcare is being increasingly recognized. It is crucial for the patients to be heard about how they experience e-PHRs and health IT in general as they receive care and manage their health (Feldman, Bhavsar, & Schooley, 2019). e-PHRs are widely used to promote self-management, and thus the association between their utilization by patients and patient opinion regarding care quality becomes critical to success of healthcare system (Peacock et al., 2017).

The link between e-PHR utilization and patient's perception of care quality may be explained by the principles underlined in affordances theory (Gibson, 2000). Grounded in the ideas of ecological psychology, affordance theory has been applied in variety of fields, including healthcare, technology, engineering, and education (Strong et al., 2014). An important tenet of this theory is that individuals have different perceptions about the objects in their environment. These perceptions include not only what an object is, but also what potential uses it affords, thus the origin of the word 'affordance' (Merolli, Gray, & Martin-Sanchez, 2013a). In case of technologies, affordances constitute and describe the fundamental properties or features of a technology being used by end-users to align with their specific goals. When users engage with a system with capabilities or features that help them achieve their goals, they are more satisfied (Strong et al., 2014). Better the alignment between the user's goal-oriented actions and technology capabilities, higher the positive experience of users with the technology (Anderson & Robey, 2017; Chatterjee, Moody, Lowry, Chakraborty, & Hardin, 2020). For example, when individuals with chronic conditions utilize features of e-PHRs that facilitate accomplishing self-management activities, their opinion about the care extended to them may be higher due to their positive experience with e-PHRs.

Prior studies (Qahri-Saremi, Mueller-Luckey, Robinson, Hadidi, & Sattovia, 2018; Strong et al., 2014) have focused on the concept of affordances in context of healthcare. Affordances of online medical records has been linked to the facilitation of clinicians' work practices and general improvement in service quality (Anderson & Robey, 2017). In another study, users' perception related to affordance of an EHR system in outpatient settings referred to their awareness that the system can manage and track their medication orders and whether they can make sense of this information and use it to improve their decisions relevant to their health (Qahri-Saremi et al., 2018). Affordances of social media tools and functionalities that enable communication processes tailored to user needs for effective chronic disease management are also examined (Merolli, Gray, & Martin-Sanchez, 2013b). Different affordances and outcomes from using service robots in hospital settings are identified in another study. End-users recognized the informational benefits of using service robots in hospitals as an affordance since they generated reliable information to carry out their work, thus increasing service quality in the hospital (Mettler, Sprenger, & Winter, 2017).

As chronic disease patients use e-PHRs for tasks such as refilling medications, downloading personal health information, and making decisions about their health, their expectations about how the features of e-PHRs or its affordances should support their task of managing their health conditions may shape their perceptions of health outcomes (Strong et al., 2014). This shaping of user perceptions, often referred to as actualization of technology affordances in use, is an outcome of actions taken by users as they appropriate the advantages of one or more affordances extended by e-PHRs to achieve control of their own health (Strong et al., 2014).

Previous studies (Griffin, Skinner, Thornhill, & Weinberger, 2016; Kruse, Bolton, & Freriks, 2015) show that patient access to e-PHRs promotes their ability to manage their own health, consequently improving health outcomes. It is suggested that PHR access alone does not increase patient satisfaction as much as providing access to health information via PHRs (Wagner et al., 2012). A review of literature (Kruse et al., 2015) conducted to examine the link between patient portal use and quality of care reveal that that due to lack of design features, portals are not effective enough to improve care quality and involve the patient in the medical decisions. Further, more empirical studies need to be conducted to understand the effect of portal use on patient satisfaction. Studies also found that patients who did not recognize a positive impact on their self-managed care while using e-PHRs did not perceive a positive impact on quality of care either (Khaneghah et al., 2016). A meta-analysis of several studies of the impact of e-PHRs (Otte-Trojel et al., 2014) suggests multiple mechanisms, such as patient insight into information, information activation, and accessibility have positive impact on patient's health related behavior and satisfaction. Indeed, patient engagement is cited as the one of the major benefits of e-PHRs (Kruse et al., 2015). Engaged and knowledgeable patients are more likely to embrace pre-emptive health-related measures and adopt healthy practices leading to improved health outcomes. Such patients may hold a positive opinion of the healthcare they receive (Renedo & Marston, 2015).

While some studies (Wagner et al., 2012) suggest e-PHR use does not impact individual perception of care quality, several others show that e-PHRs offer convenience, with users feeling more in control of their care (Woods et al., 2017). Patients who refill medications, access their clinical notes and test results may increase adherence to treatments and self-care. Thus, repeated and sustained use of e-PHR features may lead to increased perceptions of care quality. Therefore, we posit the following:

Hypothesis 1: An individual's use of e-PHRs is positively associated with perceived healthcare quality.

2.3 Asynchronous E-communication and Perceived Healthcare Quality

Asynchronous e-communication such as email messages and texts, most commonly used in clinical practice, enables chronic disease patients to augment their interactions with their healthcare providers to exchange information about their health and manage their own disease conditions. It allows care providers to understand the patients' perspectives and build a shared understanding of their health problems and treatment options (Antoun, 2016; Bao et al., 2020; Garrido, Meng, Wang, Palen, & Kanter, 2014). Such modes of communication are often considered a convenient complement to in-person visits while still maintaining a record of the patient-provider interaction.

While the use of asynchronous e-communication between patients and care providers have become an accepted means for interaction (Bao et al., 2020), research regarding its effect on patient perception of healthcare quality continues to evolve. Some studies cite positive relationship between e-communication and quality of care (Antoun, 2016; Garrido et al., 2014). In general, patients are more willing to engage in the use of asynchronous e-communication, show higher level of engagement with their personal health, are able self-manage their conditions, and exhibit overall satisfaction (de Jong, Ros, & Schrijvers, 2014; Xiao, Sharman, Rao, & Upadhyaya, 2014). Despite these, some inherent disadvantages exist, too. Providers are usually skeptical regarding the effectiveness of asynchronous e-communication in meeting patient needs and expectations (Antoun, 2016). Patients may feel it creates psychological distance with their providers (Hogan et al., 2018). E-communication may also increase physician's workload, partly due to the fact that the content and socioemotional tone need to be very context specific (Hogan et al., 2018). In spite of the general consensus that patient needs and preferences should be incorporated in the interactions, standards and guidelines as to what constitutes a good communication process between the patient and provider are still severely lacking (Lee, Matthias, Menachemi, Frankel, & Weiner, 2018).

Recent research (Tan & Yan, 2020) suggests that the effectiveness of asynchronous e-communication can be explained using the lens of media synchronicity theory (Dennis, Fuller, & Valacich, 2008). This theory focusses on the degree to which individuals work together towards a shared meaning as supported by the communication medium. It posits that the effectiveness of communication depends on two fundamental processes – conveyance and convergence. Conveyance refers to the act of sending information to be processed later, while convergence refers to the process of repeated interaction involving verification, validation, and discussion to achieve a shared meaning. The theory posits that tasks requiring convergence necessitates a high degree of synchronicity – the degree to which communication takes place in real-time since the goal is to achieve consensus through repeated interactions. On the other hand, tasks requiring conveyance may not need a high degree of synchronicity, as there is no need for immediate feedback.

Online patient-provider communication may involve tasks with varying levels of complexity and urgency. For situations involving simple and non-interactive communication such as scheduling appointment, electronic media with less synchronicity is appropriate. However, for more complex situations such as understanding possible drug interactions or choosing a treatment option for a patient with chronic conditions, communication with more synchronous medium (e.g., in-person meetings) are preferred. This is supported in a recent study on training diabetes patients to perform critical self-management tasks (Damali, Fredendall, Miller, Moore, & Dye, 2021).

Given that most e-communication mediums such as emails and texts are not interactive in nature and thus lack features of synchronicity, one could expect that they may not be able to appropriately fulfil a patient's needs for communicating with a provider, which in turn, will lead to lower perceptions of healthcare quality. Suggested context-specific customization (Hogan et al., 2018) is time-consuming and expensive to achieve in these mediums. Provider hesitancy (Antoun, 2016) may further reduce the perception of healthcare quality of the individual with chronic illness. Therefore, we posit the following:

Hypothesis 2: A patient's asynchronous e-communication with provider is negatively associated with their perception of healthcare quality.

2.4 Moderating Effects of Multiple Chronic Conditions (MCC) and Generation

As indicated previously, the relationship between e-PHR utilization and use of asynchronous e-communication with the perception of healthcare quality may be influenced by higher healthcare needs such as for patients with MCC and generational differences in technology usage patterns (Irizarry et al., 2015). These arguments are presented in the following sections.

2.4.1 Moderating Effect of MCC

Patients with MCC may experience a range of severities that can create complex healthcare needs not experienced by those with only one chronic condition (Reed et al., 2019). Individuals with MCC may require more procedures, visits, and routine lab tests to keep track of their health status (Safford, Allison, & Kiefe, 2007; Yamin et al., 2011). They may also need to coordinate health information from different providers and monitor and distinguish between symptoms from different diseases and associated severities (Zulman et al., 2014). This creates a higher "burden of treatment" (Reed et al., 2019) due to the demands on a patient's time and energy as well as other relevant aspects of self-care (e.g., health monitoring, diet, exercise).

Based on the underlying view of technology affordance framework (Anderson & Robey, 2017), e-PHRs may act as an effective technology solution for such patients (Reed et al., 2019). Affordances arise from the association between the technology and the 'goal orientation' of the actor (patient with MCC) who may be appropriating specific features of e-PHRs that support their ability to manage the complications linked to having several chronic conditions. For example, compared to patient with one chronic condition, a patient with MCC has a greater need to use a e-PHR functionality that enables sharing health information with multiple specialists.

Studies have shown that patients with MCC use e-PHRs in higher proportions due to higher healthcare needs (visits, lab tests) to keep track of their health status (Safford et al., 2007; Yamin et al., 2011) and are more sensitive towards e-PHRs utilization as it provides a better feedback loop for self-care and disease management (Reed et al., 2019). Increased use of e-PHRs for management of MCC is also shown to be associated with higher level of trust (Lyles et al., 2013), which may act as a precursor to patient engagement, ultimately leading to improved opinion regarding healthcare quality.

In summary, OHMT such as e-PHRs may help reduce the "burden of treatment" for patients with MCC. Consequently, these individuals may perceive higher quality of care with more utilization of e-PHRs, given their greater need for online health management to support self-care. Therefore, we hypothesize:

Hypothesis 3a: The relationship between individual's use of e-PHRs and perceived healthcare quality is moderated in such a way that patients with MCC will perceive higher quality of healthcare.

Patients with MCC experience competing demands for their healthcare, and for that, they have to usually self-prioritize their illnesses based on their own perceived health condition. This can complicate their e-communication interactions with providers and impact their psychological well-being, particularly when patients and providers do not agree on which health-related problems are most important to address, or how to address them (Reed et al., 2019). For the management of MCC, prescribed approaches for one condition may be contraindicated for another, or several medications may be needed to effectively treat a single condition. For example, an individual with diabetes and heart disease, vigorous physical activity such as running may be advised by the provider for diabetes management but may be infeasible due to heart ailment.

Healthcare literature has advocated for constructing complex communication models that includes MCC, along with socio-economic and other conditions, in order to increase the congruence between patient-provider interactions (Hogan et al., 2018). There is evidence to suggest that having MCC reduces the perception of effectiveness of patient-provider interactions, and patients rate these communications lower (Street, Makoul, Arora, & Epstein, 2009). Scholars have highlighted limitations in existing e-communication tools and called for re-designing them to allow patient-provider communication based on the importance placed on different disease conditions (Magnan et al., 2015). Based on the above arguments, we hypothesize the following:

Hypothesis 3b: The relationship between individual's asynchronous e-communication with provider and perceived healthcare quality is moderated in such a way that patients with MCC will perceive lower quality of healthcare.

2.4.2 Moderating Effect of Generation

Prior research (Lyles et al., 2013; Walker et al., 2020) has cited age or generation to be a significant factor in determining utilization of e-PHRs. Some studies (Riippa et al., 2014) have shown that older adults (those born prior to 1980) face significant hurdles in using e-PHRs while completing routine healthcare tasks due to reasons such as computer literacy, access, and cognitive ability (Walker et al., 2020). Thus, e-PHR utilization may reduce with patient's age. A study by Clarke et al 2020 (Clarke et al., 2020) found that young adults (between 19 and 39 years) have a high utilization rate for e-PHRs due to convenience while middle-aged adults (between 40 and 64 years) and their senior counterparts (individuals 65 years and above) do not feel the same way. The extent of e-PHR use among two age groups - 18 to 54 years old and 55 years and above- were compared (Luo, Dozier, & Ikenberg, 2021). The study found inclusion of clinical notes to be positively related to e-PHR use among both age groups. Accessing e-PHRs using a smartphone app was associated with higher e-PHR use among younger adults while ease of understanding health information in e-PHRs was linked to higher e-PHR use among older adults. The use of a patient portal by a population of patients with diabetes with significant self-management demands was examined (Sarkar et al., 2011). Individuals (above 40 years) were less likely than their younger counterparts (40 years or below), to request a password to use the patient portal, suggesting that problems with internet access, or differences in acceptance of portal use, may contribute to disparities in use between the two age groups. Notably, among those who had sufficient computer access to request a password for the patient portal, older adults were more likely to log on than younger users, perhaps because of their increased healthcare and self-management needs.

Although they may experience considerable difficulties in accessing and using e-PHRs, one of the groups that have the potential for greater acceptance of e-PHRs due to their 'mounting' healthcare needs (Walker et al., 2020) are older adults (born prior to 1980) with chronic condition(s). They recognize and appreciate the potential benefits of e-PHRs for better engagement with their own health and are seen to place higher trust with e-PHR systems and provide higher satisfaction ratings (Lyles et al., 2013). It can be argued based on technology affordance theory that higher levels of utilization of features of e-PHRs will lead to increased satisfaction among older adults with chronic conditions (Chatterjee et al., 2020). As this group of individuals utilize e-PHRs for tasks such as refilling medications, accessing personal health information, and making care decisions, their opinion about e-PHRs may improve, which then could shape their perceptions of quality of the healthcare (Strong et al., 2014). Therefore, we hypothesize the following:

Hypothesis 4a: The relationship between individual's e-PHR utilization and perceived healthcare quality is moderated by generation in such a way that an individual from the older generation perceives higher quality of healthcare.

It is well known that there exists a "digital divide" due to age (Lyles et al., 2013). While older generations (group of individuals born before 1980) may appreciate features of e-PHRs more than millennials and later generations (individuals born after 1980), their expectations regarding asynchronous e-communication may also vary due to the digital divide between them (Lyles et al., 2013; Yamin et al., 2011). Among several socio-economic and educational factors contributing to the digital divide, generation, especially the differences in terms of attitude, expectation, and usage play a major role (Prensky, 2001). In the context of healthcare, there is a relative lack of understanding as to how these differences may shape the relationship between asynchronous e-communication and the perception of healthcare quality.

The main difference between older generations (those born before the year 1980) and the younger millennials and subsequent generations (individuals born after 1980) is that the latter group, being exposed to different digital technologies from very early stage of their lives are much more absorbed in a networked world. More importantly, they have a clearly distinct pattern of adoption and continued usage (Kesharwani, 2020) of technology and are active users seeking interactivity through the digital medium. Whereas, individuals belonging to the older generation are rather passive users whose main purpose is functionality (Kesharwani, 2020). Conceivably, the younger generation (millennials and later generations) would perceive asynchronous e-communication to be lacking in richness and immediacy. In other words, leveraging on explanations provided by media synchronicity theory, the lack of synchronicity of the mode of communication will be felt more by the younger generation rather than the older population.

An individual's choice to use technology can be formed via two ways (Kesharwani, 2020). First, by developing extrinsic motivation, that is improvements in belief judgments through experience. Second, by emergence of intrinsic motivation, that is, to develop a habit. This may imply that there will be difference in perceptions between older generations and the younger group of individuals (or millennials, born after 1980) as they continue to use asynchronous e-communication tools. Since the older generations' primary purpose is functionality, continued usage may result in higher satisfaction and subsequently higher perception of healthcare quality. Therefore, we hypothesize the following:

Hypothesis 4b: The relationship between individual's asynchronous e-communication with provider and perceived healthcare quality is moderated by generation in such a way that older generation perceives higher quality of healthcare.

Based on the aforementioned hypotheses, our conceptual model is shown in Figure 1.

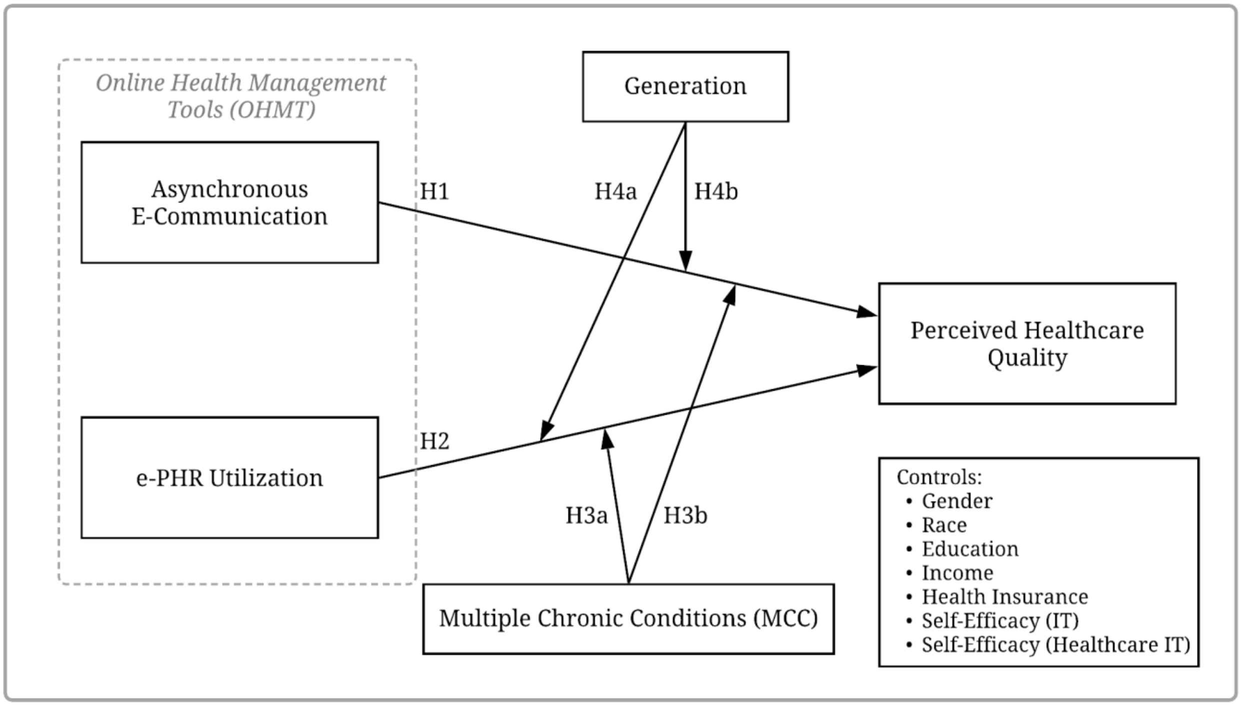

Figure 1. Research Model

3 Method

3.1 Data Source

To test the proposed hypotheses, this study used data from National Cancer Institute (NCI)'s Health Information National Trends Survey (HINTS), a nationally representative, cross-sectional survey of non-institutionalized US adults aged 18 years or older, administered every 1-2 years since the year 2003. The survey gathers public data on a broad range of health-related topics to understand trends about access to health information as well as the use of OHMT to communicate with health providers. Previous health information systems research (Venkatesan, Abdelhamid, Monteiro, & Sharman, 2016; Xiao et al., 2014) has also used HINTS data to understand online information seeking behavior of individuals and how that impacts heath management and outcomes.

This study utilized data from the first 2017 wave of the most recent HINTS data collection cycle (HINTS5). The sampling frame used two explicit sampling strata containing US addresses with high and low concentrations of minority population and then oversampled the high-minority strata to increase the precision of estimates for minority subpopulations. After scanning, verification, cleaning, and editing of the received responses through mail, the sample contained 3,203 observations and has an overall response rate of 32.39%.

3.2 Measurements

e-PHR utilization was operationally defined as the extent of an individual's usage of e-PHR system with respect to its key functions including the following: (a) making appointments, (b) refilling medications, (c) filling out paperwork, (d) correcting information, (e) look up test results, (f) monitoring health, (g) downloading health information, (h) adding health information to share with their healthcare provider, and (i) making treatment decision regarding an illness or health condition. These nine dichotomous items align with common e-PHR use cases (Lyles et al., 2013; Otte-Trojel et al., 2014). The summative score of these binary choice questions was used to derive an index for measuring the extent of e-PHR utilization.

Asynchronous e-communication with healthcare provider was defined as the extent to which one communicated electronically with their healthcare provider or staff within the past year. Aligned with prior studies, three dichotomous measurement items were used (Antoun, 2016; de Jong et al., 2014; Hogan et al., 2018), asking whether the respondent (a) communicated with a healthcare provider using electronic means, (b) sent/received text from a healthcare provider, and (c) shared health information through smartphone with a healthcare professional. The responses were summed to create an index (0-3) on the construct with a higher score indicating more and diverse use of asynchronous e-communication options.

Generation was defined as the different generational categories: Millennials (Generation Y, born between 1980 and 1994), Generation X (Gen X, born between 1965 and 1979), Baby Boomers (born between 1946 and 1964), and Silent Generation (born between 1928 and 1945) (Berkowitz & Schewe, 2011). These categories, computed based on the respondent's reported age, capture the differences in computer literacy and corresponding different usage patterns of digital devices and the Internet. The Millennial generation is generally regarded as the first to grow up in an environment with increasing digital access, and are often referred to as the "digital natives" (Prensky, 2001). The generation categories also capture the birthrate rise and declines over the years. For example, 1965 was the first year that the birthrate started to decline following the baby boom between 1946 and 1964. Similarly, 1980 marked the birthrate increase following the decline in birthrate in prior years.

Multiple chronic conditions (MCC) construct was described as the co-existence of several chronic health conditions (Zulman et al., 2014). According to the US Centers for Disease Control and Prevention (CDC), diabetes/high blood sugar, heart disease and stroke, and cancer are the three leading chronic diseases in the US with six in ten Americans known to have at least one of these three chronic conditions (Centers for Disease Control and Prevention, n.d.). Respondents were asked if they were ever diagnosed with these chronic conditions. Based on the responses to these binary choice questions, a derived variable measured whether the respondent had multiple chronic conditions or not.

Perceived healthcare quality, the dependent variable in this study, was defined as the respondent's perception of overall healthcare quality. This construct was measured with a single item. Single items are acceptable if the question is unambiguous (Wanous, Reichers, & Hudy, 1997) and has been used in information systems research in healthcare (Abdelhamid, Gaia, & Sanders, 2017; Angst & Agarwal, 2009; Xiang & Stanley, 2017). Following an approach similar to a previous study (Xiang & Stanley, 2017), respondents were asked to rate the quality of healthcare they received in the past year on a five-point scale, which was then reverse-coded (1 = poor to 5 = excellent) for this study. Please refer to Appendix A for a detailed questionnaire, scale and their usage in this study.

3.3 Control Variables

Demographic, health-related variables, and self-efficacy were used as controls. Respondent's gender was recoded as 0 = female, 1 = male. Race was originally measured using a series of dichotomous questions about 14 different races, recoded as 1 = white, 2 = black, 3 = other for this study. Education was measured on a seven-point scale (1 = less than 8 years to 7 = postgraduate), recoded as 1 = less than high school, 2 = 12 years or completed high school, 3 = some college. Household income was measured on a nine-point scale (1 = less than $10K to 9 = $200K or more), recoded as 1 = less than $10K, 2 = $20K to less than $50K, 3 = $50K to less than $100K, 4 = $100K to less than $200K, and 5 = $200K or more. Health insurance coverage of respondents was recoded as 0 = no, 1 = yes. Self-efficacy with information technology (IT) was measured with a summative score using six binary choice questions, and then recoded as 0 = none, 1 = low, 2 = medium and 3 = high. Similarly, self-efficacy with healthcare technology was measured with a summative score of nine binary choice questions and then recoded similar to self-efficacy with IT. Arguably, self-efficacy with IT and health technology are related, yet distinct. While the former focuses on comfort with general IT, the latter focuses on the user's comfort with OHMT such as e-PHRs. Please refer to Appendix A for a detailed questionnaire, scale and their usage in this study.

3.4 Missing Data

In large survey-based secondary datasets such as HINTS, it is typical that many participants do not complete the entire questionnaire, resulting in missing responses to many questionnaire items. Commonly used single imputation procedures like list wise deletion (complete case analysis) are problematic due to issues such as sample size reduction and biases introduced in the statistical estimates (Graham, 2009). Alternatively, multiple imputation procedures are advantageous for handling missing data since they fill in the missing values by accounting for uncertainty in the imputations and yield accurate statistical estimates (Graham, 2009). They operate under the assumption that the missing data are Missing At Random (MAR) and create multiple predictions for each missing value based on observed data (van Buuren & Groothuis-

Oudshoorn, 2011). This research adopted the multivariate imputation by chained equations (MICE) method to replace the missing values (van Buuren & Groothuis-Oudshoorn, 2011).

4 Results

Descriptive statistics for the variables used in the study are shown in Table 1.

Table 1. Descriptive Statistics

Variable	**Frequency (Percentage)[a] or Mean (SD)[b]**
Gender	Male (= 1): 1,287 (40.18%), Female (= 0): 1,916 (59.82%)
Race	White: 2,278 (71.12%) Black: 600 (18.73%) Other: 325 (10.15%)
Education	Less than high school: 210 (6.56%) 12 years/completed high school: 631 (19.70%) Some college: 966 (30.16%) College graduate/higher: 1,396 (43.58%)
Income	< 20K USD: 571 (17.83%) 20K USD to < 50K USD: 932 (29.10%) 50K to <n 100K USD: 994 (31.03%) 100K to < 200K USD: 533 (16.64%) More than 200K USD: 173 (5.40%)
Health insurance	Yes (= 1): 3,050 (95.22%), No (= 0): 153 (4.78%)
Self-efficacy with information technology	1.57 (0.90) (min = 0, max = 3)
Self-efficacy with health technology	1.61 (0.95) (min = 0, max = 3)
Multiple chronic conditions (MCC)	Yes (= 1): 268 (8.37%), No (= 0): 2,935 (91.63%)
Generation (GEN)	Millennials/Gen Y (= 0): 439 (13.71%) Gen X (= 1): 740 (23.10%) Baby Boomer (= 2): 1,491 (46.55%) Silent (= 3): 533 (16.64%)
E-PHR utilization (EPU)	0.68 (0.83) (min = 0, max = 3)
Asynchronous e-communication (with healthcare provider) (AEC)	0.84 (0.94) (min = 0, max = 3)
Perceived healthcare quality (PHQ)	4.06 (0.85) (min = 1, max = 5)

Note: ‘a’ Represents frequency (percentage) for a categorical variable and ‘b’ represents mean (standard deviation) for a continuous numeric variable.

Multicollinearity relates to the linear relationship between independent variables that can introduce potential bias in their model coefficients (Alin, 2010). The multicollinearity issue was analyzed by computing the variance inflation factor (VIF) statistics. VIF for an independent variable represents the increase in variance of that variable’s regression coefficient due to multicollinearity. As shown in Table 2, the VIF for all principal variables in the study was well below 5.0, alleviating multicollinearity (Hair, Anderson, & Tatham, 1995) concerns. Additionally, correlation coefficients for the independent variables were analyzed as shown in Table 3 to assess multicollinearity. All correlations were below 0.5 and the highest correlation coefficient was noted to be 0.40 between e-PHR utilization and asynchronous e-communication with healthcare provider. Since all correlations were below the acceptable threshold of 0.6 (Hair et al., 1995), multicollinearity was not a concern for this analysis.

Table 2. Variance Inflation Factors

Variable	**EPU**	**AEC**	**MCC**	**GEN**
VIF	2.14	1.71	1.07	1.32

EPU: e-PHR Utilization
AEC: Asynchronous E-Communication with Healthcare Provider
MCC: Multiple Chronic Conditions
GEN: Generation

Table 3. Correlation Matrix for Independent Variables

	EPU	AEC	MCC	GEN
e-PHR Utilization (EPU)	1.00			
Asynchronous E-Communication with Healthcare Provider (AEC)	0.40	1.00		
Multiple Chronic Conditions (MCC)	0.01	0.02	1.00	
Generation (GEN)	-0.16	-0.12	0.21	1.00

Given that the data was gathered through a single survey instrument and self-reported by participants, we examined the possibility of bias due to common method variance (CMV), which could affect the estimated relationships between the variables (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). We examined CMV bias using a marker variable technique (Lindell & Whitney, 2001). The variable, frequency of using a tanning bed or booth in the past year (TAN) (refer Appendix A for the questionnaire), was selected as a marker variable since it is theoretically unrelated to any of the principal variables in the study. The correlation of the marker variable with the study variables in shown in Table 4. The low correlation values, below the threshold value of 0.1 (Lindell & Whitney, 2001), between the marker variable and the study variables indicate the absence of CMV.

Table 4. Correlation with Marker Variable

Variable	**PHQ**	**EPU**	**AEC**	**MCC**	**GEN**
Correlation with Marker Variable 'Frequency of using tanning bed or booth'	0.00	0.02	0.03	-0.03	-0.07
p-value	0.99	0.22	0.14	0.14	0.00

PHQ: Perceived Healthcare Quality
EPU: e-PHR Utilization
AEC: Asynchronous E-Communication with Healthcare Provider
MCC: Multiple Chronic Conditions
GEN: Generation

Prior to hypotheses testing, we assessed the homogeneity of error variance assumption used when analyzing the data using moderated multiple regression (Aguinis & Gottfredson, 2010). We analyzed the data for the two categorical moderator variables: multiple chronic conditions (MCC) and generation (GEN) using Levene's test (Brown & Forsythe, 1974) that is robust under nonnormality conditions. Three test statistics are used to assess in-group equality of variance: Levene's test statistic (W0) uses mean while Brown and Forsyth's modified statistics uses median (W50) and 10% trimmed mean (W10) as alternative location estimators to compute the test statistic. For MCC, the test-statistics and p-values are as follows: W0 = 2.55 (0.11), W50 = 1.26 (0.26), W10 = 0.92 (0.34), and for GEN, the test-statistics and p-values are as follows: W0 = 1.35 (0.26), W50 = 1.55 (0.20), W10 = 1.57 (0.19). In both cases, the p-values are not significant indicating that there is not a statistically significant difference in the perceived healthcare quality between different levels of each categorical variable.

Hypothesis testing was conducted using moderated multiple regression (Aguinis & Gottfredson, 2010). Models were adjusted for gender, race, education, household income, health insurance coverage, self-efficacy with IT, self-efficacy with health technology. The factors self-efficacy with IT and self-efficacy with health technology are expected to be somewhat related (moderate correlation coefficient of 0.5). Analysis included the use of sample weights from the survey data to analyze weighted population estimates and replicate weights to compute standard error of estimates using the jackknife replication method. Table 5 shows the estimation results.

Table 5. Moderated Multiple Regression Analysis Results

	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
e-PHR Utilization (EPU)	0.0351* (0.0497)	0.0789 (0.0474)		-0.1491* (0.0739)		-0.1676* (0.0938)
Asynchronous E-Communication (AEC)	-0.0708** (0.0284)		0.0886** (0.0294)		-0.0269 (0.0528)	0.0601 (0.0731)
Multiple Chronic Conditions (MCC)		0.4654*** (0.1090)	0.4990*** (0.1127)			0.5138*** (0.1196)
EPU X MCC		-0.2603* (0.1057)				-0.2217* (0.1283)
AEC X MCC			-0.2491* (0.0942)			-0.1707* (0.1126)
Generation (GenX)				-0.2288* (0.1159)	-0.1254 (0.1138)	-0.2380* (0.1186)
Generation (Baby Boomer)				-0.0781 (0.0642)	0.0207 (0.0836)	-0.0922 (0.0675)
Generation (Silent)				0.0410 (0.0912)	0.1264 (0.1022)	-0.0266 (0.0959)
EPU X GenX				0.2843** (0.0889)		0.2841** (0.1097)
EPU X Baby Boomer				0.2720*** (0.0746)		0.2838** (0.1105)
EPU X Silent				0.2722** (0.0910)		0.2826** (0.1172)
AEC X GenX					0.1383* (0.0733)	0.0013 (0.0961)
AEC X Baby Boomer					0.1213* (0.0577)	-0.0029 (0.0932)
AEC X Silent					0.1395* (0.0711)	0.0412 (0.0933)
Constant	3.9576*** (0.1666)	3.8721*** (0.1661)	3.8796*** (0.1565)	3.9869*** (0.1812)	3.9172*** (0.1929)	3.9511*** (0.1845)
Controls: Gender, Race, Education Income, Health Insurance, Self-efficacy (IT), Self-efficacy (healthcare technology)	Yes	Yes	Yes	Yes	Yes	Yes
R-square	0.0459***	0.0524***	0.0550***	0.0635***	0.0566***	0.0764***
Sample size	3203	3203	3203	3203	3203	3203

Note: * p < 0.10, ** p < 0.01, *** p < 0.001
PHQ: Perceived Healthcare Quality
EPU: e-PHR Utilization
AEC: Asynchronous E-Communication with Healthcare Provider
MCC: Multiple Chronic Conditions
GenX: Generation X
Baby Boomer: Baby Boomer Generation
Silent: Silent Generation

Analysis from Model 1 shows e-PHR utilization (β = 0.0351, p < 0.10) to be positively associated, while asynchronous e-communication with healthcare provider (β = -0.0708, p < 0.01) to be negatively associated respectively with perceived healthcare quality, thus supporting both hypotheses 1 and 2. Models 2 and 3 examine the moderation effect of MCC. With Model 2, the relationship between e-PHR utilization and perceived healthcare quality is found to be dependent on the presence of MCC, however in the opposite direction of hypothesis 3a (β = -0.2603, p < 0.1), establishing a negative impact of MCC on the relationship between e-PHR utilization and quality perception. Conversely, Model 3 provides support (β = -0.2491, $p < 0.10$) for hypothesis 3b. Models 4 and 5 examine the moderation effect of generation. Model 4 shows strong support for hypothesis 4a. Using Millennials as the comparison group, the results indicate quality perception of individuals belonging to this generation is negatively associated with higher e-PHR utilization and the trend is opposite to that of the older generations. Model 5 also analyzes hypothesis 4b using Millennials as the comparison group. Results show that as the extent of asynchronous e-communication increases, the older generations, i.e., GenX (β = 0.1383, $p < 0.10$), Baby Boomer (β = 0.1213, $p < 0.10$), and Silent (β = 0.1395, $p < 0.10$) perceive healthcare quality to be better compared to the Millennial cohort.

Model 6 shows the results of analyzing the variables and interactions from prior models together to test hypotheses 3 and 4 in a combined manner. Hypotheses 3a and 3b are supported as before. However, only hypothesis 4a is supported, but not hypothesis 4b. Considering the results of models 5 and 6 together, we argue that hypothesis 4b is only partially supported. Finally, the homoscedasticity assumption of the residuals was assessed using White's test (White, 1980), which yielded a p-value of 0.12 and thus the null hypothesis of homogeneity of the variance of the residuals was not rejected. Table 6 provides a summary of the results.

Table 6. Summary of Results

Dependent Variable: Perceived Healthcare Quality (PHQ)			
Hypothesis	**Independent Variable**	**Moderator**	**Result**
H1	e-PHR Utilization (EPU)		Supported
H2	Asynchronous E-Communication with Healthcare Provider (AEC)		Supported
H3a	e-PHR Utilization (EPU)	Multiple Chronic Conditions (MCC)	Not Supported
H3b	Asynchronous E-Communication with Healthcare Provider (AEC)	Multiple Chronic Conditions (MCC)	Supported
H4a	e-PHR Utilization (EPU)	Generation	Supported
H4b	Asynchronous E-Communication with Healthcare Provider (AEC)	Generation	Partially Supported

A slope analysis was conducted to assess whether the gradient is significantly different from zero (Cohen, Cohen, West, & Aiken, 2013). From the interaction plots in Figures 2-5, the hypothesized directions are supported by the significant interactions shown. Figures 2, 3, and 5 are based on Model 6, while Figure 4 is based on Model 5. Figure 2 depicts that the relationship between e-PHR utilization and perceived healthcare quality reverses direction, i.e., becomes negative in the presence of MCC. It is evident from Figure 3, that patients with MCC e-communicating asynchronously with their healthcare provider perceive lower quality of care, as compared to their counterparts without MCC. Figure 4 shows that for Millennials, perceived healthcare quality decreases with increased e-PHR utilization. This trend seems to be reversed in case of the older generations, GenX and Baby Boomers. Similarly, from Figure 5, it is observed that for Millennials, perceived healthcare quality decreases with increased frequency of asynchronous e-communication with provider. Again, this trend seems to be reversed in case of the older generations, GenX and Baby Boomers.

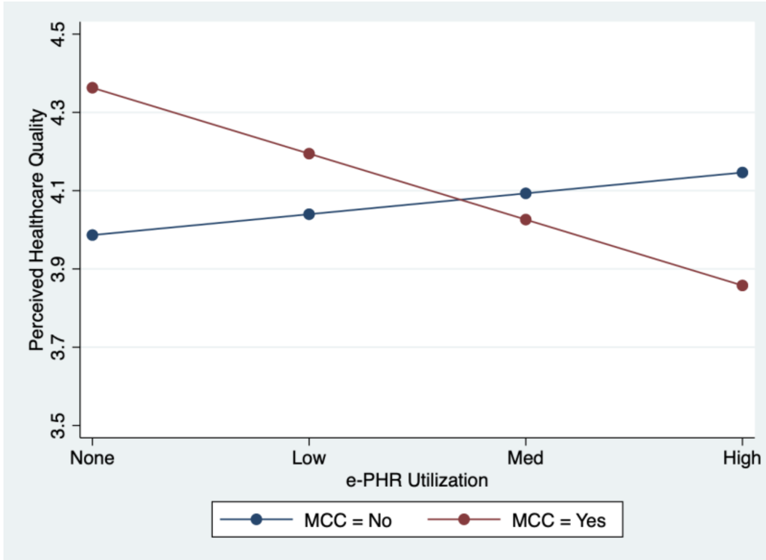

Figure 2. Predictive Margins of e-PHR Utilization X MCC

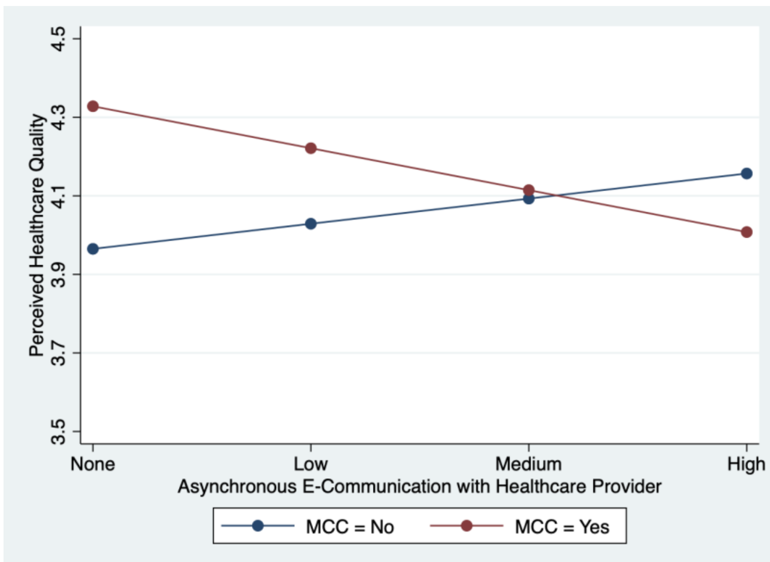

Figure 3. Predictive Margins of Async. E-Comm. X MCC

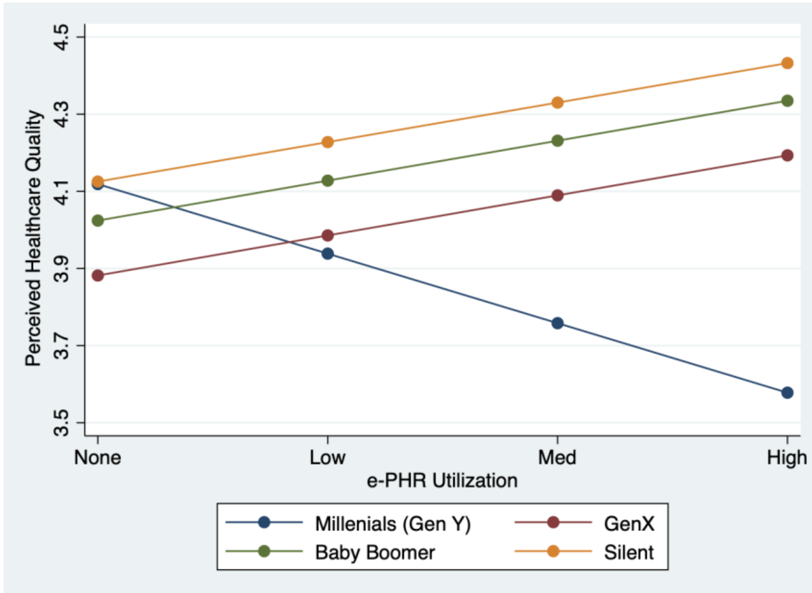

Figure 4. Predictive Margins of *e-PHR Utilization X Generation*

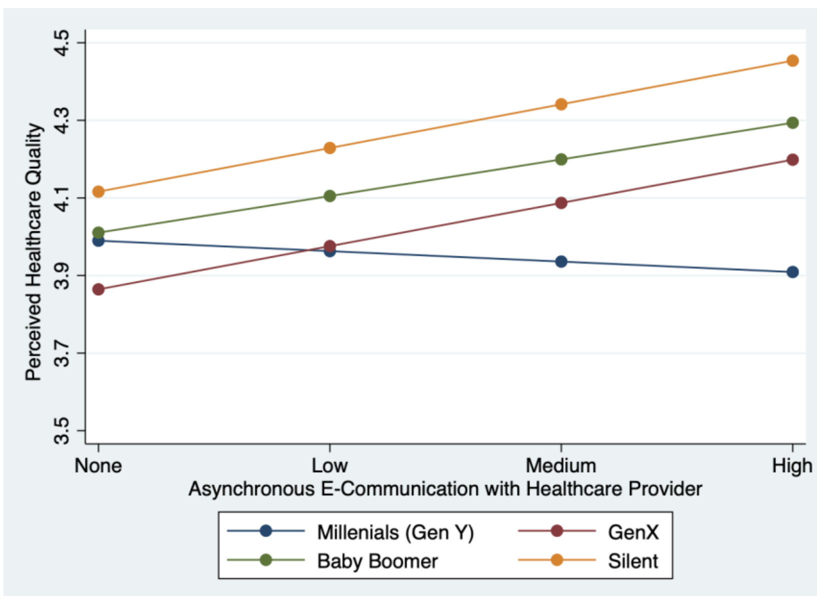

Figure 5. Predictive Margins of Async. E-Comm. X Generation

5 Discussion

Using technology affordance and media synchronicity frameworks, this study examined how OHMT, specifically e-PHRs and text/email-based e-communication impacts care quality perception of individuals, and how their health complexity and generation may affect such relationships. As expected, our findings provide support for the positive association between e-PHR utilization and individual perception of healthcare quality. Higher usage generally led to a more positive view of care received. However, contrary to our expectations, the direction of the relationship was reversed for patients with MCC. Also, as hypothesized, patients' generation is seen to affect the relationship between e-PHR utilization and healthcare quality, with millennials showing reduced perception of quality while older generations show opposite trend.

The affordances provided by most e-PHRs currently in use are the ability to perform routine tasks including refilling medications, accessing and managing personal health information (Abd-alrazaq et al., 2019). However, patients with MCC often have complex care needs due to interrelated nature of their underlying health conditions (Zulman et al., 2014). Contrary to our hypothesis, our results show reduced perception of healthcare quality with MCC, is a possible indication that current e-PHRs lack the features necessary to handle multifaceted tasks such as balancing diets and exercise based on diagnostics for different chronic conditions. Also, in situations where an individual sees multiple providers and thus may end up using different e-PHRs, the interrelatedness of different health issues may not be captured well in e-PHRs. In other words, our findings suggest that while current e-PHR functionalities might adequately support the needs for patients with one or no chronic condition, they are not yet sufficient for those with more complex clinical needs. In summary, our results provide some encouragement that e-PHRs are a great first step towards higher perceived care quality. However, they also highlight the need for interoperability and further enhancement of e-PHR features and capabilities to carry out complex clinical tasks.

As expected, generational effects were significant on the relationship between e-PHR utilization and care quality. Using millennials (i.e., digital natives) as the baseline for comparison, our study shows a distinct difference between this group with older generations. Interestingly, while our overall hypothesis that digital immigrants (Gen X and older) will have higher perception of healthcare quality with increased e-PHR use is supported, it is remarkable to see that millennials perception of healthcare quality *reduces* with increased use. This is possibly because digital natives (millennials and the younger generations) have a higher expectation from technology-driven solutions. With repeated use, the flaws in the systems become more apparent, leading to lower perception of overall healthcare quality. Older generations, on the other hand, may have a higher threshold of tolerance for inadequacies that exist in healthcare systems due to greater familiarity with its shortcomings based on a lengthier history of dealing with it (Kruse et al., 2015). These are similar to our findings for hypothesis H4b (partially supported).

As predicted by media synchronicity theory, results lend support to the relationship between asynchronous e-communication and healthcare quality to be negative. E-mails and text messages, the two prevalent methods of asynchronous e-communication, may be ideal for carrying routine tasks, such as scheduling appointments, reminders for appointments or taking medications. However, they are quite deficient where the underlying task requires some level of convergence, i.e., creating a common understanding, such as making behavior and/or lifestyle changes. As expected, patients with MCC perceive an even less quality of healthcare when using asynchronous e-communication. We have partial support that individuals belonging to GenX, baby boomer, and the silent generations (i.e., digital immigrants) have a better perception of healthcare quality compared to digital natives (or millennials) while using these asynchronous e-communication tools. These results support our argument that lack of commensurate, relevant, and context-specific information due to the asynchronous nature of the interaction may render the communication process less effective, especially where clinical complexity is higher (Lee et al., 2018; Xiang & Stanley, 2017).

The finding that the relationship between patient use of asynchronous e-communication and their perception of quality was positive and significant for GenX and older (digital immigrants) is noteworthy. Even though we find partial support for this hypothesis (supported in model 5, but not in model 6), the results bear striking similarity to the relationship between e-PHR and healthcare quality. Younger generations (millennials/ digital natives) regard asynchronous e-communication not only to be less effective and inefficient as compared to the individuals in older age groups (the digital immigrants), but also their satisfaction *reduces* with increased asynchronous e-communications, possibly due to differences in technology usage and expectation between these generations. Below, we discuss the theoretical and practical implications of our study.

5.1 Theoretical Implications

Our work provides theoretical contribution in understanding the relationship between use of OHMT and perceived healthcare quality by introducing health complexity and generation as theoretically derived set of moderators. While extant research has predominantly focused on adoption and access related issues regarding OHMT, how these factors interact with OHMT has not yet been explored in healthcare information systems research.

The introduction and subsequent validation of these moderators make further contributions to both theoretical frameworks from which they were derived – technology affordance and media synchronicity – by adding a more nuanced view of the underlying constructs and their relationships. Such nuances include contextual factors as well as user characteristics. The moderating effect of MCC on the relationship between e-PHR utilization and individual perception of care quality provides specific insight into the role of contextual factors in how individuals link affordances to the fulfillment of their tasks. While our study highlights this nuanced relationship in healthcare research, the role of relevant context specific factors in how users perceive technology affordances should be explored in other domains as well. Further, the moderating impact of character traits (generation) on the relationship between asynchronous e-communication and care quality perception adds to the body of knowledge relevant to media synchronicity. More precisely, convergence may be very sensitive to contextual complexity as seen in the case of patients with MCC requiring a higher degree of synchronicity for communication. Similar contextual factors may be relevant in domains other than healthcare as well. On the other hand, conveyance may have differential impact based on user characteristics as we see that digital natives (or millennials) are even less perceptive to asynchronous e-communication compared to digital immigrants.

5.2 Practical Implications

It is encouraging that increased use of e-PHR tools leads to better healthcare quality. As digitization becomes the norm in every aspect of life, it is essential that tools for health management and self-care achieve their intended purpose. This comes with some caveats, though. First, for patients with MCC, who have more complex healthcare needs when compared to patients with one chronic illness (Zulman et al., 2014), the effectiveness e-PHR tools is lacking. The same is true for digital natives or millennials who do not seem to enjoy the same benefit with increased e-PHR use. The implications of these findings point to future design upgrades not only to incorporate features that integrate among different e-PHRs to provide a comprehensive and user-friendly tool, but also to do so in such a way that meets the expectations and usage patterns of the younger digital natives.

Study results suggest that asynchronous e-communication such as text or email do not support the richness needed for nuances and appropriate inputs from providers about treatment strategies to converge well (Ko, Bratzke, & Roberts, 2018). This is even more salient for patients with MCC. For example, an individual with diabetes, heart disease, and cancer may need to be advised to prioritize close monitoring of blood sugar and blood pressure levels and accommodate insulin and/or medication doses as needed over physical activity on a day the individual underwent chemotherapy. In many ways, lack of directed consultations over text or email may leave individuals with MCC frustrated with the communication process, thus reducing their perception of quality of care. Further efforts are required towards educating both patients and providers. Providers may need to set clear expectations about the role of e-communication, and its appropriateness as a medium for patient-provider interaction. Healthcare system developers would need to ensure that asynchronous e-communication includes capabilities to enable meaningful, richer, and contextually more specific patient-provider interactions. Also, ‘guided’ telehealth consultations or virtual visits may act as supplements to asynchronous e- communication in specific scenarios.

Finally, the differential impact of generation on the relationship between OHMT - that digital natives’ perception of healthcare quality follows a reverse trend with increased use of both e-PHR and asynchronous e-communications - bear significant implications for future design and updates of such technologies. It is well-known that digital natives (or millennials) interact in different ways with technology when compared to the older generations or digital immigrants (Kesharwani, 2020), whose expectation may be less from technology-enabled processes (Magsamen-Conrad & Dillon, 2020). Further, because of their relative level of comfort with regards to using technology, digital natives may be more likely to consult resources outside those provided by OHMTs and are less likely to rely solely on the content from their provider. These behavioral differences are crucial for designers and developers of OHMT as the digital natives grows older since the likelihood for developing MCC increase with age.

6 Conclusion

This study contributes to the stream of research on effectiveness of OHMT for chronic care management and extends our understanding of the drivers of healthcare quality as affected by two separate constructs – e-PHR utilization and asynchronous e-communication. Our results are encouraging for healthcare providers and patients in terms of the use of e-PHRs. At the same time, it also illuminates the deficiencies of the current e-communication mechanisms. Of special note is the moderating effect of MCC. While extant literature has noted that chronic conditions require greater level of technology-enabled support in managing individual’s healthcare needs (Laugesen & Hassanein, 2017), our findings illuminate the divergence in expectations for people with MCC compared to those with single chronic condition. Our work provides further insights into the effect of generation on the efficacy of both e-PHR tools and e-communication methods. In this respect, issues regarding digital literacy and access are commonly recognized. The current study adds to this literature by illustrating that quality perceptions vary between digital natives and immigrants and underlines the need for enhancing the current features and capability of e-PHR and e-communication tools to account for generational differences relevant to expectation from technology.

This study has limitations. First, the model included two factors – use of e-PHRs and asynchronous e-communication for patient-provider interaction as determinants of individual perception of healthcare quality. Other factors, such as competence of the provider, or patient's own health outcome, could also determine care quality and should be explored in future studies. Second, the study was limited in scope as it did not include wearables, which are now considered most frequently used OHMT. While inclusion of wearables was not possible due to the non-availability of relevant data, it will be worthwhile for future studies to explore their effect on care quality perceptions. Third we also recognize that the data used in this research predates the COVID-19 pandemic, which somewhat forced digital literacy/greater comfort with technology on many users in different walks of life. As our results suggest, individuals with complex healthcare needs are not supported well with current OHMT, post-pandemic OHMT usage data would provide opportunities for future research as to whether and how these relationships may change post-pandemic. Fourth, we recognize the possibility of reverse causality in the proposed model and it would need to be investigated further in a future study. Finally, another limitation of our study was that provider's response time during e-communication with patient may influence patient's perception of quality (Yang, Zhang, & Lee, 2019). However, there is lack of relevant data to examine the nuances of how perceptions of quality may vary based on the provider's response time.

The US healthcare system is burdened by the ongoing rise in chronic diseases and will increasingly require patients to take ownership of their own health (Bao et al., 2020). OHMT have the potential to enable patients to do so (Hogan et al., 2018; Tabatabai, 2013). However, their efficacy and usage trends among chronic disease patients belonging to different generations will largely depend on how well these digital tools are customized and aligned to meet patient-specific needs. Future studies should explore the effectiveness of enhanced digital solutions, for example, tele-monitoring systems that have the functionality to feed providers with regular inputs about the patient's condition. Research should also explore design elements in digital solutions that inspire individuals across generations to collaborate in the care management process.

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Appendix A: Operationalization of Constructs (Source: HINTS 5 Cycle 1)

Construct	Question	Scale	Coding
e-PHR Utilization (EPU)	In the past 12 months, have you used your online medical record to…	Yes or No	For each e-PHR function, respondents answered Yes (=1) or No (=0). The summative score recoded from 0 to 3 was used: 0: None (=0) 1: Low (=1-2) 2: Medium (=3-6) 3: High (=7-9)
	(a) Make appointments with a health care provider		
	(b) Request refill of medications		
	(c) Fill out forms or paperwork related to health care		
	(d) Request correction of inaccurate information		
	(e) Look up test results		
	(f) Monitor your health		
	(g) Download your health information to your computer or mobile device		
	(h) Add health information to share with your health care provider, such as health concerns, symptoms, and side-effects		
	(i) Help you make a decision about how to treat an illness or condition		
Asynchronous E-Communication with Healthcare Provider (AEC)	In the past 12 months, have you used a computer, smartphone, or other electronic means to e-mail or the use the Internet to communicate with a doctor/doctor's office?	Yes or No	For each question, respondents answered Yes (=1) or No (=0). The summative score was used: 0: None 1: Low 2: Medium 3: High
	Have you sent or received a text message from a doctor or other health care professional within the last 12 months?		
	Have you shared health information from either an electronic monitoring device or smartphone with a health professional within the last 12 months?		
Generation (GEN)	What is your age?	Number	Based on the respondent's age, the generation was recoded: 0: Millenials or Generation Y 1: Generation X 2: Baby Boomer 3: Silent
Multiple Chronic Conditions (MCC)	(a) Has a doctor or other health professionals ever told you that you had diabetes or high blood sugar?	Yes or No	For each question, respondents answered Yes (=1) or No (=0). The summative score was recoded for whether the respondent had multiple chronic condition: 0: No (=0-1) 1: Yes (=2-3)
	(b) Has a doctor or other health professionals ever told you that you had a heart condition such as heart attack, angina, or congestive heart failure?		
	(c) Have you ever been diagnosed as having cancer?		
Perceived Healthcare Quality (PHQ)	Overall, how would you rate the quality of health care you received in	1: Excellent 2: Very good	1: Poor 2: Fair

	the past 12 months?	3: Good 4: Fair 5: Poor	3: Good 4: Very good 5: Excellent
Gender	Are you male or female?	Male or Female	0: Female 1: Male
Race	What is your race?	White, Black, and other races (not listed here)	0: White 1: Black or African American 2: Other
Education	What is the highest grade or level of schooling you completed?	1: < 8 years 2: 8-11 years 3: 12 years or high school 4: vocational or training (not college) 5: Some college 6: College graduate 7: Postgraduate	0: Less than high school 1: 12 yrs or high school 2: Some college 3: College graduate or higher
Income	What is your combined annual income from all sources earned in the past year?	1: < \$10K 2: \$10K to < \$15K 3: \$15K to < \$20K 4: \$20K to < \$35K 5: \$35K to < \$50K 6: \$50K to < \$75K 7: \$75K to < \$100K 8: \$100K to < \$200K 9: \$200K or more	0: < \$20K 1: \$20K to < \$50K 2: \$50K to < \$100K 3: \$100K to < \$200K 4: \$200K or more
Health insurance	Are you covered by health insurance or a health coverage plan?	Yes or No	0: No 1: Yes
Self-Efficacy with Information Technology	Do you ever go on-line to access the Internet or World Wide Web, or to send and receive e-mail?	Yes or No	For each IT ability, respondents answered Yes (=1) or No (=0). The extent of self-efficacy with IT is the sum of the values, varying from 0 to 6.
	In the last 12 months, have you used the Internet to visit a social networking site, such as Facebook or LinkedIn?		
	In the last 12 months, have you used the Internet to share health information on social networking sites, such as Facebook or Twitter?		
	In the last 12 months, have you used the Internet to write in an online diary or blog (i.e., Web log)?		
	In the last 12 months, have you used the Internet to participate in an online forum or support group for people with a similar health or medical issue?		
	In the last 12 months, have you used the Internet to watch a health-		

	related video on YouTube?		
Self-Efficacy with Healthcare Technology	In the past 12 months, have you used a computer, smartphone, or other electronic means to do any of the following…	Yes or No	For each healthcare technology ability, respondents answered Yes (=1) or No (=0). The extent of self-efficacy with healthcare technology is the sum of the values, varying from 0 to 9.
	(a) access your online medical record		
	(b) looked for health or medical information for yourself		
	(c) looked for health or medical information for someone else		
	(d) Bought medicine or vitamins online		
	(e) Looked for a healthcare provider		
	(f) Make appointments with a healthcare provider		
	(g) Track health care charges and costs		
	(h) Filled out form or paperwork related to your healthcare		
	(i) Look up test results		
Tanning Booth or Bed (Marker Variable)	How many times in the past 12 months have you used a tanning bed or booth?	0: 0 times 1: 1-2 times 2: 3-10 times 3: 11-24 times 4: 25 or more times	0: Never 1: Rarely 2: Sometimes 3: Often 4: Always

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