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Exploration of Health Technology Nonuse: The Case of Online Medical Records

Surma Mukhopadhyay
Independent Researcher, iamsurma@gmail.com

Ramsankar Basak
University of North Carolina at Chapel Hill, rams@email.unc.edu

John P. Bentley
University of Mississippi, phjpb@olemiss.edu

Saurav Mukhopadhyay
Northern Illinois University, saurav@niu.edu

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Surma Mukhopadhyay
Independent Researcher
Durham, North Carolina, United States
iamsurma@gmail.com

Ramsankar Basak
University of North Carolina at Chapel Hill
Chapel Hill, North Carolina, United States
rams@email.unc.edu

John P. Bentley
Pharmacy Administration, University of Mississippi
Oxford, Mississippi, United States
phjpb@olemiss.edu

Saurav Mukhopadhyay
Educational Technology, Research, and Assessment
Northern Illinois University
Dekalb, Illinois, United States
saurav@niu.edu

Abstract

Online Medical Records (OMR) platforms remain a key enabler to health management. Yet, how beliefs toward OMR and its subsequent nonuse are related is not understood. Applying the status quo bias (SQB) theory and the privacy paradox paradigm the study examines OMR nonusers and contributes to the health technology use literature. Using the Health Information National Trends Survey (HINTS) iteration 5, Cycle 1 and 3 data, mediation analysis reveals that inertia expressed as preference for speaking directly with healthcare providers predicts perceived need for OMR and partially mediates the relationship between perceived privacy concerns and need; having a chronic disease partially moderates such relationships. Thus, not all nonusers are created equal. Attaining benefits that come with capabilities and functionalities of OMR necessitates meaningful use of OMR by individuals. Healthcare providers or policymakers should intervene to dispel inertia or patient concerns to expand OMR use to facilitate healthcare decision making.

Keywords: Patient portals, status quo bias, inertia, privacy, need, nonuse, chronic disease

Introduction

Online medical records (OMR) systems, which are also referred to as patient portals and electronic personal health records (ePHR), are promising tools that enable individuals to conveniently and efficiently engage in their health-related activities, including interacting securely with health care providers, accessing test results, or performing other self-management activities (Angst & Agarwal, 2009; Tavares & Oliveira, 2016). Although many care providers have been reported to make OMR available to their patients, a sizeable number of patients remain *nonusers* (Tavares & Oliveira, 2016). Many studies have been conducted to examine user acceptance of patient portals but few have focused on *nonusers*. Because initial acceptance of information systems (IS) does not guarantee continued use (Bhattacherjee, 2001), we do not distinguish between nonadopters and nonusers following adoption (together herein described as *nonusers*) because both cases result in individuals failing to utilize the full benefits of OMR. As a result, there is a considerable need to understand patients who have remained nonuser of OMR. Specifically, to our knowledge, how attitudes and/or beliefs toward OMR are interrelated has not yet been studied and as such, this precludes a deeper understanding of nonuse of OMR.

Factors that prohibit patient OMR use are many. Privacy-related concerns, an important barrier to adoption, include unwarranted commercial use, data release to potential employers, or protecting sensitive mental health records (Hamamura et al., 2017; Nahm et al., 2018; Nguyen et al., 2014). A relationship exists between privacy and security concerns and attitude toward technology (Gurung & Raja, 2016; Kisekka et al., 2021); negative attitude is among the dominant factors that deter the adoption rates of OMR (Emani et al., 2016; Latulipe et al., 2015). Some enablers (e.g., usefulness) are reported to counteract negative impacts (Cochran et al., 2015); the privacy paradox phenomena and other contextual effects (e.g., post-adoption user satisfaction) have diluted the importance of privacy concerns (Kokolakis, 2017; Li et al., 2017). However, residual privacy concerns related to OMR still remain (Kisekka, 2021). Thus, how privacy concerns affect nonuse decisions warrants further attention.

Consumer reluctance to adopt new technology has been studied (Kim & Kankanhalli, 2009; Suri et al., 2013; Wu, 2016). Transitioning to a new IS may be associated with technological discomfort or change-related fears and contribute to the rejection of the OMR adoption or use (Alvand, 2015; Gesulga et al., 2017). Forcing a new IS onto individuals can potentially result in individuals being reluctant to utilize OMR (Dinev et al., 2016). Furthermore, it has been suggested that patients are not likely to use OMR if the system fails to closely align with their attitudes and expectations (Greenhalgh et al., 2010). Although past studies are useful for explaining individuals' technology adoption behaviors, significant gaps in understanding of nonuser perspectives remain. Who among all nonusers are attitudinally close to acceptance? What are the variables that might alone or together sway nonuser attitudes? As users and nonusers are not on the polar opposite spectrum, further examining nonuse is needed to fill a critical void in the health technology literature. We note that OMR use does not require mandates (e.g., employer policy) or is not part of routine tasks for an individual's daily life. As such, characteristics necessitate reexamining antecedents and relationships in the current context.

Building on past research and the Status Quo Bias (SQB) theory (Li et al., 2021; Polites & Karahanna, 2012; Samuelson & Zeckhauser, 1988), the current study aims to understand how inertia and privacy concerns affect perceived needs for OMR. As such, an understanding should help enhance OMR adoption rate and provide insights into the factors that help drive OMR use or potentially minimize future nonuse. A better understanding of the relationships will lead to efficiency in having care providers select interventions targeted to OMR adoption or use. This study not only focuses on nonusers but also asserts that not all nonusers are equal. Thus, some may be relatively more easily persuaded to use OMR than others. A more nuanced understanding will be valuable and useful to health care services providers and policymakers to develop customized strategies and messages when communicating with patients.

Literature Review

Perceived Need for Use of a New Technology

The progress through the adoption/use decision stages starts with the recognition of the need for a product/service (Teng, Lu, & Yu, 2009). Perceived need is positively associated with intention to adopt or purchase mobile services (Hashim et al., 2015). In health-related contexts, the addition of perceived need to the Theory of Planned Behavior (TPB) largely improves the prediction of intention to undertake healthy behavior (Paisley & Sparks, 1998; Payne et al., 2004). Hsiao & Tang (2015) find a relationship between perceived need and attitude toward the usage of mobile healthcare technology. Paisley & Sparks (1998) emphasize that need will likely be reflected in cognitive attitude (i.e., perceived benefit), but is distinct from cognitive attitude. Perceived need has also been regarded as a motivational construct in research examining technology innovation adoption (Wang et al., 2018). One's self-motivation, an innate human psychological status, is found to significantly drive one's health needs (Ryan & Deci, 2000). Conceptualization of perceived need reflects the difference between perceptions of needs and actual health needs (Teng, Lu, & Yu, 2009; Wang et al., 2018). Yet, perceived need for OMR among nonusers has received little attention.

Prior studies have examined antecedents of perceived need. Lin et al. (2015) show a relative advantage to having a positive influence on perceived need for mobile service adoption. Relative advantage—regarded as one of the most important innovation characteristics impacting innovation adoption (Choudhury & Karahanna, 2008)—implies the extent to which adopting innovation is perceived to be better than continuing the system it supersedes (Venkatesh et. al., 2003). Costs to be incurred to switch to a new system have a negative influence on perceived need for the system (Wang et al. 2018). In addition, benefit loss costs (e.g., skills and familiarity with the current system) occur when individuals leave the current system for an alternative (Burnham et al., 2003). Such perceived loss of benefits that individuals currently enjoy with current use patterns results in lower perceived need (Wang et al., 2018). User inertia is found to negatively affect perceived need for fitness app and perceived need not only has a positive effect on apps exploration intention but also mediates the relationship between inertia and apps exploration intention (Li et al., 2021); hence, perceived need reveals the force that inertia may exert. Yet, the state of need perceptions among nonusers of OMR has not been adequately investigated.

Inertia and Status Quo Bias

The SQB perspective (Samuelson & Zeckhauser, 1988) has been extensively applied as a theoretical foundation in IS research on user resistance that is manifested as individuals' failure to switch from an incumbent technology or system to a one newly introduced (for a review, see Kim & Kankanhalli 2009; Wu, 2016). SQB (also described as “status quo inertia”) exerts an inhibiting effect on switching behavior (Samuelson & Zeckhauser, 1988). Inertia induces a bias in favor of the current or previous status or course of action; indeed, inertia behaviors are not only present in switching to or evaluating a new IS but also pervasive in different stages of diffusion of information technology (Samuelson & Zeckhauser, 1988). As such, patterns of influence weaken individuals' motivation to explore a new health technology and lead to biased assessments of the nature of health-related needs (Wang et al., 2018).

Prior studies used the SQB theory together with other theories to explain why individuals adhere to status quo choices resisting new IS options (e.g., Kim & Kankanhalli, 2009; Polites & Karahanna, 2012). Sun et al. (2017) propose that inertia is key to exerting the mooring effects associated with individuals’ switching from one mobile instant messaging application to another. Using both Warshaw's Purchase Intention Model and SQB, Wang et al. (2018) show that inertia has a negative role in information technology upgrade. Based on theories of cognitive dissonance and consistency, Polites & Karahanna (2012) assert inertial individuals’ cognitive misperceptions result from their efforts to maintain cognitive consistency and greatly reduce cognitive dissonance. Thus, inertia alone or in concert with other factors may continue to exert its impact on key constructs prohibiting IS use.

Samuelson & Zeckhauser (1988) assert three mechanisms through which the status quo effects prevail. The first is rational decision making which implies that individuals undertake an assessment of relative costs to switch. Costs as antecedents of inertia include procedural switching costs, uncertainty costs, benefit loss costs (Wang et al., 2018; Li et al., 2021). Second is cognitive misperceptions of loss aversion; as individuals tend to assess potential losses as higher than potential gains that are likely to occur if they switch to alternatives, loss aversion tendency will result in SQB (Samuelson & Zeckhauser, 1988). Third, psychological commitment leads to SQB and includes sunk cost and control preference (Samuelson & Zeckhauser, 1988). To explore the effects of SQB factors on online health services use, Zhang et al. (2017) conceptualized overall perceived benefits and overall perceived costs while the former was driven by sunk cost and the latter by transition costs and privacy protection beliefs.

Privacy Concerns

In the context of IS use, privacy concerns can directly or indirectly influence behavior or intention; when individuals perceive that their privacy is not protected from violations (e.g., unauthorized collection or use or dissemination of information) they associate a risk with using the system and may make decisions to not engage with the system or to limit their level of engagement accordingly (Smith et al., 2011). However, individuals continually engage in adjustment processes in which privacy concerns are weighed against other factors (e.g., personal communication); indeed, context-driven situational forces are found to moderate or be directly associated with the nature and the extent of privacy-related relationships (Sheehan 2002; Smith et al., 2011). Privacy and security issues have a negative effect on patient intentions to use mobile health (mHealth) apps (Aliad et al., 2019). With privacy concerns, one would be cautious about health information sharing through web applications and would rather go to providers directly. Privacy and security concerns are found to be a general obstacle, in spite of consumers' willingness to adopt consumer health informatics for self-management of health (Laxman et al., 2015). Angst & Agarwal (2009) find information privacy concerns to be an important determinant of attitude to use EHR. Park & Shin (2020) note effects of privacy concern and confidence on engagement are mediated through interest in sharing data with care providers. Similarly, performance expectancy of patient portals was found to mediate the privacy concern effect on use intention (Abd-Alrazak et al., 2019).

There are many facets of privacy associated with health data control. Park & Chung (2017) proposed privacy as sociotechnical assets that may serve to encourage and empower individuals to effectively take on health data-related tasks; health privacy capital positively affects the level of digital interactions with healthcare professionals and depicts the extent of positive views one holds. On the contrary, behavioral economics prescribes cost perspectives of taking protective measures when one makes decisions about privacy. For example, McDonald & Cranor (2008) point out that it was burdensome for one to weigh in privacy statements of websites because no one liked investing time reading or evaluating the policy; as such, perceived costs led to behavioral consequences of non-action. High levels of concerns may diminish individuals' interest in certain behavioral actions (e.g., digital engagement) depending on contexts or attributed values of information (Kokolakis, 2017; Park & shin, 2020). Privacy concerns generally predict privacy-related attitudinal beliefs or intentions (Gerber, et al., 2018; Li et al., 2017). Evidence of paradoxical behaviors exists and it is certain that individuals do undertake cost-benefit analysis (or privacy calculus) while making decisions related to privacy (Lee et al., 2013; Kokolakis, 2017); however, privacy and its complex web of relationships among OMR nonusers have not been explored well.

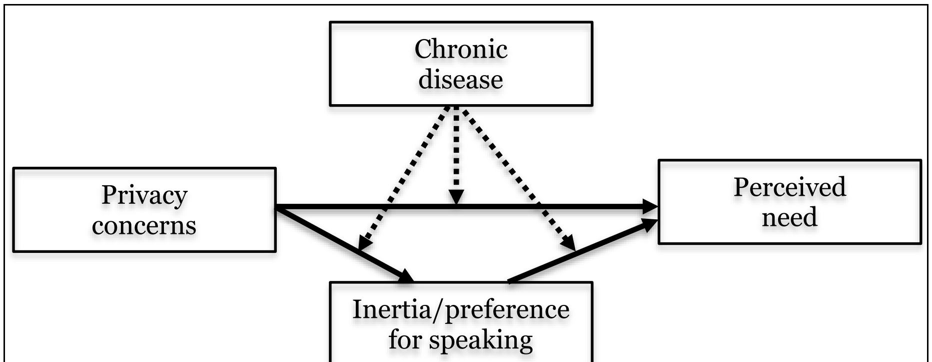

Figure 1. Conceptual Model

Conceptual Model and Hypotheses

Inertia as Preference for Speaking Directly and Perceived Need

The focal construct proposed to be associated with attitudinal beliefs about OMR is inertia (see Figure 1). In prior research, individual-level inertia has been defined as "attachment to, and persistence of, existing behavioral patterns even if there are better alternatives or incentives to change" (Polites & Karahanna, 2012, p.24). While some posit habit as a subconscious source of inertia others have conceptualized inertia as persistence of habit (Polites & Karahanna, 2012). Habits enable individuals to defer to the status quo (Samuelson & Zeckhauser, 1988) as individuals may find it difficult to control or lack resources to adapt to changes; in fact, it is not unusual for an individual to view existing habits as beneficial as the individual does not have to make changes to routinized behavior. Although routines are not habits (Limayem et al., 2007), a routine that is repeated frequently over time may become a habit. As a consequence, ongoing habits lead to behavior-based inertia (Polites & Karahanna, 2012). Of other components of inertia, the cognitive component reflects conscious decisions to continue to use an existing system of doing things even if the current course of action is not perceived as most efficient or effective for a given task, while the affective component reflects an emotional attachment to or enjoyment or comfort in doing things in the current way (Polites & Karahanna, 2012). Once satisfied, individuals continue to perform ongoing behaviors to avoid any potential undesired states associated with alternatives, which demand resources for the assessment of how those fit individuals' needs or routines (Polites & Karahanna, 2012). As such, an assessment may be stressful and lead one to underassess or downgrade the value of alternatives and rather become more committed to current behavioral patterns.

Many patients are used to seeking or managing care through traditional routes such that they seek to talk to providers or feel comfortable with the existing mode of communication or management process (i.e., favoring speaking directly). Explaining individuals' propensity to resist change, Polites & Karahanna (2012) contend that individuals show a preference to seek routines such as a preference for familiar situations with limited novelty; furthermore, individuals are prone to stress associated with a change that is not self-initiated. Inertia occurs as a conscious judgment that is developed due to individual feeling comfort from continuing an existing situation (Balakrishnan et al., 2021) or due to behavioral impetus. Thus, if the traditional way of care management has been through direct interaction with providers, anything different will compromise comfort. As inertia is the persistent use of the existing system (Wang et al., 2018), inertia is the underlying latent driver of a specific behavioral pattern and manifested in preference to interact directly in the current context.

Within the technology acceptance literature, it is not much discussed whether nonusers are a homogeneous group. We propose not all nonusers are created equal. Our rationale is that some nonuser patients are more involved in their healthcare than other nonusers. For example, some patients have a higher preference for information-seeking and will have a stronger tendency to foster positive views about accepting e-health technology that facilitates receiving additional healthcare (Hsiao & Tang, 2015). Such a distinction may be unfolded in differential perceived need for use of new technology. In the field of IS, perceived need is construed as a motivational element affecting IS adoption (Wang et al., 2018). We argue there are differential perceived needs among nonusers characterizing their differential innate psychological status just as is found with users' psychological status during the exploration of fitness app (Wang et al., 2018). Furthermore, Paisley & Sparks (1998) note that perceived need is likely to be reflected in cognitive attitude (i.e., perceived benefit) and the potential importance of perceived need in studying behavioral patterns. Consistent with prior research in IS (e.g., Wang et al., 2018), this study considers perceived need as a motivational factor that acts as an antecedent to acceptance. In this study, perceived need is defined as an individual's desire to use OMR based on implicit cognitive and affective assessments.

According to the Self-perception theory, individuals avoid current deliberations and rely on their past behavior to guide their perceptions; inertia makes them think if it was good enough in the past, it should be good enough now or in the future (Samuelson & Zeckhauser, 1988). Because inertial individuals tend to maintain cognitive consistency, individuals rationalize their current way of doing things by viewing alternatives negatively in order to avoid cognitive dissonance (Samuelson & Zeckhauser, 1988). Thus, inertia or engrained habit biases perceptions of a new technology downward to substantially reduce cognitive dissonance and justify the continuance of current ways of doing things. According to the SQB perspective, cognitive misperceptions of new technology magnify perceived losses of changing from using the current approach (Kim & Kankanhalli, 2009) that, in turn, results in a lowered assessment of the relative advantage of using the new system. Biased assessments of relative advantages of adoption are also the results of the uncertainty that the new system truly performs (Samuelson & Zeckhauser 1988). As such, inertia-driven deliberations affect an accurate assessment of the relative advantages or usefulness of new technology over the existing approach and justify fostering higher negative beliefs about the advantages or usefulness of new technology (Polites & Karahanna, 2012). As a result of biased assessments, it is likely that needs assessments will be similarly affected. Although OMR systems have features to provide extended benefits, inertia may prevent one from being fully willing to recognize or realize the need to explore new functionalities. Prior studies have shown that inertia downgrades perceptions of a new system (Li et al., 2021; Polites & Karahanna, 2012). Recker (2014) contends that while evaluating options, individuals distinguish between the performance advantages (i.e., positive consequences of the current and new system use) and disadvantages (i.e., negative consequences) of two competing options; beliefs about system performance are important contributors to the choice of an option. For some, prevailing inertia is more likely to diminish willingness to abandon the status quo of the current way of doing things and some individuals may put heavier utility weights on outcomes of speaking directly rather than interacting via OMR. Therefore, we posit,

H1: Preference for speaking directly (inertia) will be negatively associated with perceived need for using OMR.

Relationship of Privacy Concerns with Inertia and Perceived Need

Motives to continue existing systems or courses of action may be many. According to the SQB theory, there are costs of subconscious and conscious origins (Samuelson & Zeckhauser, 1988). For this study, we consider the conscious cost which is relevant to the current context. Rational decision-making drives conscious costs that lead to bias or inertia (Samuelson & Zeckhauser, 1988). Polites & Karahanna (2012) examine transition costs (e.g., time and/or effort needed to adapt to a new situation) and report a positive relationship with inertia. Benefit loss costs (i.e., perceived loss of potential benefits associated with incumbent systems use) positively affect inertia (Yanamandram & White, 2010). Taking on the push-pull-mooring perspective, a study by Zhang et al. (2021) finds a relationship between privacy concerns and switching behavior. Zhang et al. (2017) conceptualize overall perceived cost, of which privacy protection belief is an antecedent. The online environment generally increases privacy fears and privacy protection beliefs that privacy will be protected as promised reduce privacy concerns (Cranor, Reagle, & Ackerman, 2000; Zhang et al., 2017). In fact, privacy concerns seem to work through a trade-off between perceived benefits and risks in influencing patient adoption of EHR (Cherif et al., 2021); Lehnbom et al. (2014) report 46% believed the risk of privacy breaches is higher with EHR compared to that with paper records. Interestingly, Fox & James (2021) report that individuals with health information privacy concerns were less likely to allow their health information to be included in a EHR system because health information systems were not largely prevalent at the time of the study. Not all perceive privacy and react to issues related to privacy in the same way (Sheehan, 2002). For example, patients sometimes voice concerns about access to their information even by family members or when information is considered sensitive (Alwashmi et al., 2020; Schulte et al., 2016). An individual is likely to be more concerned about privacy when using OMR due to being in the online environment; individuals may perceive greater risks and threats to their health information in the online context (Zhang et al., 2017). A higher level of perceptions of concerns about privacy arouses greater efforts to protect information (e.g., cautious information disclosure or less comfort in sharing sensitive information). For instance, in the context of mental health, some express concerns about online records that would store health information longitudinally with a chance of being used out of context (Shen et al., 2019). As such, efforts or concerns can be treated as the potential costs of moving away from the existing practice or situation and therefore may affect cost perceptions (Zhang et al., 2017).

Privacy concerns have been found to negatively influence the behavioral intention for or attitudes toward adoption in the internet-based environment (Angst & Agarwal, 2009). As personal health data are considered sensitive, having to deal with such data raises important privacy issues compromising patient intention to use EHR (Cocosila & Archer, 2014). It is noted that evidence exists for privacy paradox in that despite privacy concerns individuals might accept EHR or privacy concerns have little effect (e.g., Fox, 2020). However, the roles of contextual differences must be noted. For example, unlike prior research, this study focuses on individuals who discontinued or did not accept OMR and privacy paradox may not be at play. Indeed, theoretical and empirical justification of contextual effects in technology adoption research has been examined (e.g., Park & Shin, 2020; Schepers & Wetzels, 2007). Thus, benefit perceptions of forsaking privacy concerns may not have outweighed cost perceptions leaving privacy concern beliefs consistent with attitudinal beliefs regarding perceived value of or need for innovation; in other words, in such a situation, privacy concerns will downgrade the need for technology. Indeed, a review paper concludes that some types of privacy concerns should be expected to exert a stronger influence on attitudinal beliefs than others (Kokolakis, 2017). We posit the following hypotheses.

H2a: Privacy concerns will be positively associated with preference for speaking directly (inertia).

H2b: Privacy concerns will be negatively associated with perceived need.

Mediating Role of Inertia

As discussed above, inertia biases perceptions of need in order to largely lower cognitive dissonance (Polites & Karahanna, 2012). That is, inertia downgrades perceived need. In addition, as discussed above, in the presence of privacy concerns (i.e., potential benefit loss or uncertainty) individuals will show increased inertia. That is, as costs/loss perceptions increase it increases inertia; as such, increases, in turn, further decreases innate motivation or perceived need for changing to a newer course of action. Polites & Karahanna (2012) emphasize such a mediation role of inertia on attitudinal beliefs (e.g., relative advantage); specifically, perceived costs of switching affect attitudinal beliefs only to the extent to which they affect the degree of inertia. If an individual perceives high privacy costs, but these costs fail to produce inertia, the individual may still recognize some needs of OMR; alternatively put, the decrease in perceived need will be less pronounced under such a scenario. Thus, we argue that inertia mediates the influence of privacy concerns on perceived need. We propose this hypothesis:

H3: Effect of privacy on perceived need will be partially mediated by preference for speaking directly (inertia) to the health care provider.

Moderating Role of Chronic Disease

Some patients with one or more of the “big five” diseases (i.e., diabetes, cardiovascular diseases, respiratory disease, cancer, and stroke) are likely to benefit from information and communication technology (ICT) use (Wildevuur & Simonse, 2015). We assert that the effect of one’s level of inertia on perceived need depends on one’s chronic disease status. An inert individual may have less motivation to fully consider and/or carefully evaluate alternatives but ongoing care needs may nudge the individual to assess perceived gain in benefit in switching. Thus, one way in which the moderating effect of chronic disease may occur is through the weakening of the relationship between inertia and perceived need.

Chronic disease could also moderate the relationship between inertia and privacy concerns. Individuals may discount some of their privacy concerns due to perceived outcomes and in turn, express an increased tendency to switch. However, the direction of influence is a little difficult to speculate. That is, the relationship between inertia and privacy concerns may be made stronger or weaker in the absence of disease. Chronic disease necessitates regular interactions with or care management decisions with providers. Thus, having a disease may encourage one to maintain the status quo but as a function of an individual’s level of privacy concerns.

Different types of privacy concerns (e.g., psychological, social, or informational privacy) explain away the paradox phenomenon (Dienlin & Trepte, 2015). Park & Shin (2020) use the ‘contextual integrity’ of privacy—distinctive social contexts influencing sets of norms and appropriateness as they relate to privacy practices, needs, and expectations—to explore one’s decision to engage or disengage with health-related digital media. This notion is contingent upon contextual appropriateness, needs, and interest. Also, individuals may fall into different categories of privacy attitude typologies (Westin 2003; Elueze & Quan-Haase, 2018). Depending on contextual attributes (cf. contextual integrity), some may not like having to disclose information, but still clearly show an understanding of trade-offs between protecting privacy and engaging with digital media (labeled as "intense pragmatist") or some may do so depending on the purpose (called "relaxed pragmatist") and some hold a fundamentalist view (i.e., very strong views about risks associated with disclosing personal information) (Elueze & Quan-Haase, 2018, p.1380). Furthermore, cognitive and emotional appraisals are dominant determinants of privacy behaviors (Li et al., 2017). Thus, individuals may have different degrees of concerning appraisals depending how sensitive they think their information is if they were to share via OMR and chronic disease and associated information sharing may sway people differently. We posit:

H4a: The relationship between preference for speaking directly (inertia) to the health care provider and perceived need will be moderated by chronic disease.

H4b: The relationship between privacy and preference for speaking directly (inertia) will be moderated by chronic disease.

H4c: The relationship between privacy and perceived need will be moderated by chronic disease.

Methodology

Data Source and Variables

The Health Information National Trends Survey (HINTS) iteration 5, Cycle 1 and Cycle 3, were used for this study. These surveys were administered to non-institutionalized US adults by the National Cancer Institute (NCI) early in 2017 and 2019, respectively. Each iteration of HINTS used a two-stage sampling design—first selecting a stratified random sample of households from a database of all non-vacant US residential addresses, including those in rural areas followed by selecting an adult respondent from each sampled household. These surveys are administered nationally and respondents are calibrated to US adult population counts by deriving person-level weights after accounting for nonresponse and noncoverage biases to the extent possible. The survey items undergo rigorous pretesting or several iterations of expert consultations and have often been used multiple times over years. This study included people who were 18 years and older. Respondents who did not access OMR in the past year were included in the study. Nonusers of OMR are those who answered a zero when asked about the number of times the respondent accessed OMR in the last twelve months.

Variable Description

Nonusers were asked about reasons for not accessing OMR with an option for binary responses (yes/no). Perceived need is the primary outcome and measured by "...having no need to access the record...". Inertia is operationalized as "... preferring to speak directly to a provider..." as the reason for not using OMR in the past 12 months. Privacy concern is measured by "...concerns about the privacy or security of the website...". The moderator used in the study is chronic diseases, which include diabetes, hypertension, heart, or lung diseases, and cancer. A binary variable is created to indicate the presence/absence of any of these diseases. Several variables are used as control variables. These are age, gender, race (White, African American (AA), or other), education (college degrees or higher, some college, or ≤high school), perceived general health status (measured by "(i)n general, would you say your health is..." on a 5-point scale), perceived ability to take self-care (measured by "how confident are you about your ability to take good care of your health" on a 5-point scale), and frequency of provider office visits (0, 1, 2, 3, 4, 5-9, ≥10 times) by the respondent within the past year (as a measure of health care use).

Statistical Analysis

We compute the overall distribution of variables. We use "causal mediation analysis" under the counterfactual or potential outcomes framework to analyze the hypothesized relationships among binary measures of perceived need, inertia, and privacy concerns. We note that such models present causal contrasts (described below) that hold only under a strict set of assumptions (Pearl 2001; Valeri & Vanderweele, 2013). Given the cross-sectional nature of this study, however, we clearly refrain from implying causality but use such terms strictly to describe the analysis as has been done in the causal mediation analysis literature. Under this framework, an effect is defined as a contrast (or difference) between potential outcomes under two different conditions for the same individual: the outcome the individual would have a) if exposed to a variable (exposure) of interest (e.g., a variable's value is set to 0 vs. 1) and b) if unexposed (Nguyen et al., 2021). This reasoning was extended to define an indirect (or a direct) effect as a contrast of two conditions defined by values of the exposure-mediator combination (Pearl, 2001). That is, the potential outcomes in a mediation model depend on both exposure values and mediator values. See Rijnhart et al. (2023) for a nice description of causal mediation analysis with binary mediators and outcomes and definitions of effect types described below. We simultaneously fit two regression models with inertia as outcome (the mediator model) and perceived need as outcome (the outcome model). Both models are fit using probit regression controlling for covariates (see Table 1 footnote for details) while the outcome model also includes inertia as a covariate. Following the above main-effects model, we repeat the same structural equation modeling (SEM) for binary groups defined by chronic disease (multigroup analysis) to test for moderating effects (e.g., test for difference between coefficients of privacy in two groups from the mediator models or alternatively said, difference in respective paths). Mplus was used to run the counterfactual method that allows decomposing the total effect into direct and indirect effects. We compute unstandardized point estimates of the quantities of interest and *P* values.

The natural direct effects assess the direct effect of the exposure on the outcome, when holding each subject's mediator constant at its potential value when assigned to either the control or treatment group (Pearl, 2001; Valeri & Vanderweele, 2013). In other words, the natural direct effects are the effects of exposure on the outcome while blocking the effect through the mediator (Nguyen et al., 2016, 2021). The pure natural direct effect (PNDE) is the contrast between two potential outcomes under different exposure values (in our case, response on privacy) while holding each subject's mediator (in our case, inertia) constant at the potential value in the control group (in our case, those not expressing privacy as a reason). In other words, the PNDE estimates the direct effect of the exposure variable (in our case, privacy) on the outcome (in our case, perceived need) while blocking any effects through the mediator (Rijnhart et al., 2023). The total natural direct effect (TNDE) measures the difference between two potential outcomes under different exposure values while holding each subject's mediator constant at its potential value in the treatment group (in our case, those expressing privacy as a reason). In other words, the TNDE is the direct effect of the exposure variable on the outcome while blocking the effect through the mediator.

Outcome	Predictor	Main-effects		No Chronic disease group		Chronic disease group	
		Est (SE)	*P*	Est (SE)	*P*	Est (SE)	*P*
Speak[a]							
	Privacy	0.906 (0.061)	<0.001	1.047 (0.094)	<0.001	0.785 (0.083)	<0.001
Need[b#]							
	Speak	0.136 (0.027)	<0.001	0.125 (0.038)	0.001	0.16 (0.038)	<0.001
	Privacy	0.202 (0.054)	<0.001	0.15 (0.086)	0.082	0.232 (0.069)	0.001

a: Model covariates: age, age X age, gender, perceived general health status, race, and education; b: Model covariates: age, frequency of visits, perceived general health, race, education, history of cancer, and perceived ability of self-care; Est: parameter estimate; SE: standard error; #: need coded as 0 (reverse coded)

Table 1: Main-effects and Group-specific Regression Model Estimates

The natural indirect effects assess the effect of the exposure on the outcome through the mediator while holding the exposure constant at the control group or treatment group value (Pearl, 2001; Valeri & Vanderweele, 2013). In other words, the natural indirect effects are the effects of exposure on the outcome through the mediator while blocking the direct treatment effect (Nguyen et al., 2016, 2021). The pure natural indirect effect (PNIE) is the contrast between two potential outcomes under different values of mediator for each subject, while holding the exposure constant at the control-group level (Rijnhart et al., 2023). In other words, the PNIE assesses the indirect effect of treatment on the outcome through the mediator while blocking the direct treatment effect by setting the exposure to 0. The total natural indirect effect (TNIE) computes the difference between two potential outcomes for which each subject's mediator value differs while holding the exposure constant at the treatment group level. In other words, the TNIE measures the indirect effect of the treatment on the outcome through the mediator while blocking the direct treatment effect by setting each subject's exposure to 1. The total effect (TE) is the difference between two potential outcomes for which both the exposure and mediator values differ.

<table>
<tr><td>Effect type</td><td colspan="6">Mediation effect</td><td colspan="3">Moderating effects
(test for group difference)[a]</td></tr>
<tr><td></td><td colspan="2">Main-effects only</td><td colspan="2">No chronic disease group</td><td colspan="2">Chronic disease group</td><td>Mediator model</td><td colspan="2">Outcome model</td></tr>
<tr><td></td><td>Est (SE)</td><td>P</td><td>Est (SE)</td><td>P</td><td>Est (SE)</td><td>P</td><td>Privacy[#]</td><td>Privacy[#]</td><td>Speak[#]</td></tr>
<tr><td>TNIE</td><td>0.017 (0.004)</td><td><0.001</td><td>0.024 (0.009)</td><td>0.007</td><td>0.013 (0.005)</td><td>0.005</td><td rowspan="5">0.262 (0.125)*</td><td rowspan="5">-0.082 (0.111)</td><td rowspan="5">-0.035 (0.054)</td></tr>
<tr><td>PNDE</td><td>0.111 (0.02)</td><td><0.001</td><td>0.088 (0.031)</td><td>0.005</td><td>0.124 (0.026)</td><td><0.001</td></tr>
<tr><td>PNIE</td><td>0.023 (0.005)</td><td><0.001</td><td>0.029 (0.01)</td><td>0.004</td><td>0.018 (0.006)</td><td>0.003</td></tr>
<tr><td>TNDE</td><td>0.105 (0.02)</td><td><0.001</td><td>0.082 (0.032)</td><td>0.01</td><td>0.119 (0.027)</td><td><0.001</td></tr>
<tr><td>Total effect</td><td>0.128 (0.02)</td><td><0.001</td><td>0112 (0.03)</td><td><0.001</td><td>0.137 (0.026)</td><td><0.001</td></tr>
<tr><td colspan="10">* P <0.05; a: the difference of the respective group-specific coefficient/path in no chronic disease group from that of chronic disease group; Est (SE): parameter estimate (standard error); #: Est (SE)</td></tr>
<tr><td colspan="10">Table 2: Mediating and Moderating Effects</td></tr>
</table>

Results

A total of 4111 subjects were included in the study. The sample consisted of 45% male, 60% White and 16% AA, 40% with a college degree or higher and 31% with some college education. The average age of participants was 57 years (standard deviation 17). These characteristics are largely representative of the demographic distribution of the population (i.e., our sample represents about 129 million adult US population by applying HINTS-provided subject-specific survey weights). A total of 55% reported having ≥1 chronic diseases (about 58 million). Of those reporting any chronic diseases, 50% reporting no need, 78% expressed speaking preference (inertia), and 28% privacy concerns; among those with no chronic disease, these numbers are 59%, 62%, and 20%, respectively.

Structural Equation Modeling Results

Main-effects Analysis

Table 1 shows the results analyzed on the combined sample. The model fit statistics are as follows: RMSEA=0.031, CFI= 0.963, and TLI= 0.815. The R-squared for regression outcomes, need and speak are 11.5% and 22.3%. All 3 paths (privacy→speak, privacy→no-need, and speak→no-need) are statistically significant ($P<0.0001$) controlling for covariates. Table 2 provides total, direct, and indirect (i.e., mediating) effects based on counterfactual principles; TNIE, PNDE, PNIE, and TNDE are all statistically significant ($P<0.0001$).

Multi-group Analysis

The results concerning multi-group analysis for the presence of chronic diseases are presented in Tables 1 and 2. All the path estimates (Table 1) are statistically significant ($P \leq 0.001$) except for the privacy→no-need path ($P=0.082$) among those without chronic diseases. The R-squared for need and speak are 12.5% and 15.5%, respectively, among chronic disease patients and 9.8% and 27.3% respectively among those without a disease. Table 2 provides group-specific total, direct, and indirect effects based on counterfactual principles; TNIE, PNDE, PNIE, and TNDE are all statistically significant ($P \leq 0.01$). Next, to test moderation by chronic disease status, we compared each of the 3 paths (i.e., privacy→speak, privacy→no-need, and speak→no-need) between groups (i.e., each statistic computed as the difference in estimate in those without any chronic disease from that with disease); only the difference between the privacy→speak path was significant ($P=0.036$) (Table 2).

Hypothesis	Supported?
H1: Preference for speaking directly (inertia) will be negatively associated with perceived need for using OMR.	Yes (Table 1 main-effects)
H2a: Privacy concerns will be positively associated with preference for speaking directly (inertia).	Yes (Table 1 main-effects)
H2b: Privacy concerns will be negatively associated with perceived need.	Yes (Table 1 main-effects)
H3: Effect of privacy on perceived need will be partially mediated by preference for speaking directly (inertia) to the health care provider.	Yes (Table 2 main-effects: TNIE/PNIE/TNDE/PNDE)
H4a: The relationship between preference for speaking directly (inertia) to the health care provider and perceived need will be moderated by chronic disease.	No (Table 2 Outcome model)
H4b: The relationship between privacy and preference for speaking directly (inertia) will be moderated by chronic disease.	Yes (Table 2 Mediator model)
H4c: The relationship between privacy and perceived need will be moderated by chronic disease.	No (Table 2 Outcome model)

Table 3: Summary of the Hypotheses

Discussion

Framed within the lens of the SQB theory and privacy paradox/contextual integrity of privacy, the present study examined the need perception for health technology (i.e., online medical records) among nonusers of the technology. Using SEM, the results provide support for five of the seven hypotheses (Table 3). Briefly, privacy perception increases inertia, which in turn downgrades need perceptions. In addition, privacy has a direct effect on need but such an effect is manifested among those with chronic diseases; this highlights how contextual conditions shape the influence of privacy in one's decisions to use health technologies.

To our knowledge, the study's hypotheses have not previously been investigated in the context of OMR; although only a few studies have explored SQB, none explores SQB and privacy related contextual integrity in the context of health technology nonuse. We posit privacy concerns as cost and integrate privacy with SQB to explain complex paths of effects on need perception. Specifically, our analysis provides evidence of the role that privacy plays. This is observed even though only a fraction (20-28%) of subjects specified privacy as a reason for nonuse. Park and Shin (2020) note a subtle but indirect influence of privacy that solves a key piece of puzzle in privacy paradox as it relates to one's decision to use digital health technologies. Our work aligns with Park and Shin (2020) but, additionally, uncovers a new path through inertia (i.e., privacy concerns differently modify inertia by one's disease status to subtly and indirectly modulate need perception). Note that unlike other contexts of consumer technology use, the current context strikingly differs in that technology use may include dealing with stressful situations (e.g., knowing about a bad test result or a new or life-threatening diagnosis). Our conceptual exploration of SQB in such a context is novel. Interestingly, a meta-analytic review on SQB in IS adoption notes that the relationship between switching cost and perceived value is underexplored (Wu, 2016). Our work in a negative context (i.e., nonuse) partially fills that void by investigating the relationship between privacy (as cost) and need if we were to assume need is related to value. Zhang et al. (2017) assess privacy as an antecedent to perceived cost of online health service use intention. We adopt a distinct approach in that we regard privacy as cost and directly measure its complex relationships with inertia, the most salient component of the SQB theory. Thus, this study enriches the SQB theory and strengthens its utility to examine OMR or similar health technology nonuse.

This study focuses on nonuse behavior and contributes to the health technology use literature. A prior study on physician rejection of electronic medical records (EMR) adoption posits that attributes of an adopter cannot be simply reversed to profile a rejecter (Schwarz, Schwarz, & Cenfetelli, 2012). In a similar vein, we argue that patients who are users and those who are nonusers are not likely at opposite ends or simply mirror images of each other. Recker (2014) proposes that intentions to continue an IS use and intentions to discontinue as distinct factors. As nonuse is a distinct behavior pattern, this study puts forth a novel conceptual framework that advances the understanding of effects of different salient reasons that drive patient nonuse of health technology. Soliman & Rinta-Kahila (2020) note individual level IS discontinuance remains a fertile ground for theory development and requires contextual research efforts. Our work should add to such efforts to develop a theoretical structure to study nonuse behaviors (although discontinuance may not completely overlap nonuse). Prior studies on OMR use by patients remain largely descriptive or exploratory (e.g., Kruse et al., 2015; Zhao et al., 2017). In contrast, this study is the first to investigate nonuser patients to provide a mechanistic view of nonuse of OMR. Inertia manifested as the preference for speaking directly with the provider has emerged as an important driver for need perceptions. As such, operationalization is novel and reflects patient beliefs that OMR would potentially insufficiently fit their requirements. Thus, this study extends our understanding of health technology nonuse decision-making by patients. Echoing Corley and Gioia (2011), this study contributes by advancing the understanding of OMR nonuse in a way that remains practically useful.

Causal mediation analysis has been around for some time now. However, its application is largely absent in information systems research or in the management information systems (MIS) literature. Sometimes, items/ variables used in MIS research are ordinal or binary and these can be analyzed with the causal mediation analysis framework as an alternative to treating them as continuous (e.g., SmartPLS treats such variables as continuous).

OMR is a key enabler for access to health services such as telehealth; thus, the study results have beneficial implications for many who are currently nonadopters, nonusers or even infrequent users. The cohort used in the current study was representative of the US population and many subjects suffered from multiple or stressful diseases in real life, including having had a cancer diagnosis in the last few years. The experience and perceptions of these subjects are overwhelmingly important and relevant from a policy standpoint, including designing outreach or holding patient-provider discussions targeted to remove ill-informed inertia and expand the portal user base. “Big five” diseases are identified as having significant individual and population-level impacts due to incidence rates or cost of management of the diseases; many have ongoing care needs due to having one or more of such chronic diseases. Globally, the prevalence of chronic diseases is on the rise and the potential of care management through the use of digital applications is immense. That chronic disease partially plays a moderating role should help customize or streamline provider-led discussions to remove mis-notions or heightened concerns; such a finding is insightful in having patients or especially those with chronic diseases utilize their online records toward better managing their care needs. To that end, patient education and digital health navigators (Rodriguez et al., 2023) could help overcome inertia or implement interventions to improve OMR usage.

The study uses binary measures, which have undergone assessments over multiple cycles of iterations. However, the binary measures have a limited ability to operationalize complex constructs such ‘need’ or ‘inertia.’ Future research should adopt measures that are operationalized on an expanded scale tied to underlying rationales. For example, inertia may be driven by amenability barriers (Joachim, Spieth, & Heidenreich, 2018), leading patient perceptions of insufficient fit of tools to requirements. Furthermore, the privacy construct has multiple dimensions (Dienlin & Trepte, 2015). Thus, the paths associated with the impact of the privacy are not fully understood. Interestingly, the privacy→no-need path was not found to be moderated by disease status. It may be that different dimensions of privacy behaviors are at play and considering these dimensions could offer a more nuanced understanding of the role of privacy concerns. Also, this study used self-reports. Such operational and conceptual issues remain important avenues for future studies to explore. Furthermore, we explored only a few antecedents or moderators of perceived need. One of the core constructs in the Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003) is social influence and this construct may play a role in nonuse behavior. Another factor that seems pertinent but was not examined is access to technology; however, a large percentage of respondents confirmed having smart devices or visited providers that maintained EMR. Future studies should investigate other constructs, including individual or systems-related factors (e.g., technology readiness, Internet access). Finally, a cross-sectional design was utilized. Future research should consider experimental designs as well as longitudinal studies.

Conclusion

Not all *nonusers* are created equal. Nonusers hold varying degrees of need for online medical records or patient portals. Inertia manifested as preference for speaking directly predicts need and partially mediates the relationship between privacy concerns and need for OMR; having a chronic disease partially moderates such relationships. Attaining benefits that come with capabilities and functionalities of OMR necessitates meaningful adoption and use—rather continued use— of OMR by individuals. Health services providers should dispel inertia or patient concerns to expand OMR use.

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