



## Full length article

## Health privacy as sociotechnical capital

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## ABSTRACT

This article identified sociodemographic factors affecting privacy surrounding health data and explored the impact of health privacy capital on the use of health-related digital technologies and related perceptions. To do so, we adopted two perspectives, (a) an individual motivational perspective derived from uses and gratifications approach and (b) a societal contextual approach from social stratification, conceptualizing health privacy as capital with multifaceted sociotechnical assets. Health privacy capital was analyzed relative to demographic, social-contextual, and medical condition variables, using the 2014 Health Information National Trends (HINTS) Survey ( $n = 3212$ ). Findings confirmed three key facets of health privacy capital—awareness of privacy, attitude toward the importance of privacy and data sharing, and confidence in the ability to maintain privacy—and multivariate regression analyses showed positive relationships between privacy capital and engagement as well as outcomes related to health-related digital technology. On the other hand, our analysis found that the development of health privacy capital is susceptible to sociodemographic disparities. For instance, a higher level of education was related to all three dimensions of health privacy capital. Interactions between education and health privacy confidence were also significant in both dimensions of health outcomes, indicating that the positive impact of health privacy confidence is moderated by the lower level of education. Practical implications for patients and healthcare professionals are discussed.

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## 1. Introduction

Public intellectuals, health officials, and technologists have acknowledged the significance of privacy with regard to health data. Maintaining privacy may play a critical role in enhancing not only the use of new health-related communication technologies but also eventual health outcomes because worried people may avoid the health system (Lohr, 2015). Few researchers have investigated the posited relationship between privacy and the use of communication technology, rarely asking how having a sense of privacy might eventually affect individual health outcomes (Li, Gupta, Zhang, & Sarathy, 2014). In particular, little agreement has emerged on the means to assess relevant dimensions of health privacy; moreover, the lack of an adequate conceptual framework has often exacerbated confusion.

## 1.1. Overview of the current study

To address these issues, this study has advanced the notion of health privacy as sociotechnical capital. Understanding privacy as capital (cf. Resnick, 2002, pp. 84–87; Uslaner, 2004; Veenstra, 2002), we borrowed insights from two strands of research: (a) uses and gratifications (e.g., Blumler & Katz, 1974; Katz & Rubin, 1981) and (b) social stratification (e.g., Coleman, 1990; Putnam, 2001). Our work built upon two theoretical assumptions. From uses and gratification, we posited that digital media consumption may derive from particular motivations and purposes of the individual's need for privacy. From social stratification, we started with the premise that individuals remain anchored in societal contexts, by their attitudes and the social interactions that shape the quality of their health. The focal point of our analysis is that privacy matters in these combined contexts, inducing productive digital interaction and connecting to or disconnecting from better health outcomes. Accordingly, we attended to discrete and multifaceted indicators of privacy when examining its consequences.

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## 2. Situating privacy as capital in the health context

Patients, healthcare providers, and researchers have long debated whether privacy and sharing personal health data affect medical treatment and services (Goldman & Hudson, 2000). Health data, by nature, are private. Revealing the boundaries of personal medical eccentricities raises the issue of the integrity of health conversations. In this vein, health privacy concerns the manner in which patients and healthcare providers can be involved in the candid exchange of ideas as well as the discussion of possible solutions and treatments (Institute of Medicine Committee on Health Research and the Privacy of Health Information, 2009).

In recent years, scholars in numerous domains have increasingly paid attention to the critical role of privacy and have taken a multifaceted approach to understanding the concept and perception of privacy in the context of health information (Hong & Thong, 2013; Kenny & Connolly, 2015). They have assessed the diverse aspects of the perception of privacy, including (a) awareness of privacy, (b) attitude toward the importance of privacy and data sharing, and (c) confidence in the ability to maintain privacy.

### 2.1. Three facets of privacy capital

First, awareness of privacy, or privacy knowledge, is a critical enabler for individuals to exercise protective actions, affecting the way they engage themselves in the full use of information technologies (Angst, 2010; Malhotra, Kim, & Agarwal, 2004). Researchers (e.g., Park & Jang, 2014; Park, 2013) have examined the extent of user knowledge of data collection and retention on the Internet and on mobile phones. Their findings have shown a dearth of public knowledge about commercial surveillance of personal data (Aquisti & Gross, 2006; for social media). Second, researchers have also documented attitudinal dimensions of privacy, such as perceived importance of sharing data (e.g., Appari & Johnson, 2010; Chin, Felt, Sekar, & Wagner, 2012; Leon et al., 2013). These studies assessed realistic situations in which people evaluated the importance of data sharing for potential medical benefits and decided to divulge data when they perceived that the benefits of health care, data security, or monetary reward outweighed potential risks of losing control over personal data (Jacobs, Clawson, & Mynatt, 2015). People are willing to disclose personal information in exchange for tangible benefits since they often understand the key tradeoff of the modern and digital economy (Rainie & Duggan, 2016). Finally, confidence in privacy, or one's ability to control and manage personal information, is another important dimension of privacy (Caine & Hanania, 2013; Malhotra et al., 2004). Confidence in privacy is a critical marker for individuals to guard against unwarranted surveillance in their engagement with data transaction (e.g., Chin et al., 2012; Turow & Hennessy, 2007).

Aligned with prior studies, we posited that privacy can be better defined, not as monolithic, but as multifaceted sociotechnical assets that enable individuals to exercise various tasks related to health data control. That is, people can possess adequate levels of "capital" (Coleman, 1990; cf.; Resnick, 2002, pp. 84–87; Uslaner, 2004) that may serve as a principle to support, encourage, and empower them to undertake health data-related tasks effectively. For instance, those with no capital may be perplexed about when to engage or interact with health professionals because they do not have appropriate reference based on which to make decisions regarding data release. In addition to the awareness or knowledge on privacy tools relating to digital health, one may not leverage digital health resources because of lack of confidence in the electronic system. Sometimes it is the attitudes one holds toward health data management that hinder one from their use. Only when people are equipped a high level of health privacy capital, they can fully use

digital health resources and ultimately, benefit from positive health-related outcomes.

This proposition is consistent with earlier studies (e.g., Appari & Johnson, 2010; Aquisti & Gross, 2006; Hong & Thong, 2013; Kenny & Connolly, 2015; Park, Campbell, & Kwak, 2012), which demonstrated the importance of privacy in its varied facets, that is, being aware, being able to negotiate and assess the benefits of revealing data, and being sufficiently confident to deal with the potential pitfalls of data. We brought these insights to the forefront of health privacy in the context of electronic medical records while integrating three key elements of privacy: (a) awareness of privacy (awareness), (b) attitude toward the importance of privacy and data sharing (importance-attitude), and (c) confidence in the possibility of maintaining privacy (confidence).

The exchange and disclosure of health information constitute the essence of medical practice beyond the doctor's office (Siegel, 1979), allowing all parties to gain knowledge, establish links, and coordinate actions to address health problems. We contend that the key features of health privacy can serve as fundamental motivation for sharing and revealing health communication in digital modes and ultimately for improving connections to health service and enhancing overall health confidence (McMullan, 2006; Wallace, 2015). In other words, health privacy capital, when adequately understood and practiced, may promote effective digital engagement because it allows for sharing medical data, opening the boundaries between individuals and healthcare professionals and shaping individual health outcomes in the process (Beard, Schein, Morra, Wilson, & Keelan, 2012; Li et al., 2014). The lack of motivation to communicate openly (Goffman, 1959) may undermine connection with others in mediated as well as traditional relationships, weakening the promise of better care.

## 3. Integrating theoretical assumptions

Some researchers (e.g., Caplan, 2003; Dutta & Feng, 2007; Stafford, Stafford, & Schkade, 2004) have suggested that uses and gratifications approach can be particularly helpful in understanding individuals' use of health-related new media. That is, differences in motivation among individuals may be the key in the patterns of media selection (Blumler & Katz, 1974; Katz, Blumler, & Gurevitch, 1973; Rubin, 1981) and in producing differentiated health outcomes (Bandura, 2005). Fundamentally, this provides the underlying rationale behind health privacy as a driving force or hindering factor in individuals connecting via various digital platforms, such as mobile, smartphones, and social media with different health purposes. They might see the importance of such data exchanges and expect gains as a result while also assessing the benefits of personal data. Extending this logic to the context of our discussion, one can see how health privacy as a significant capital resource creates incentive to seek out better engagement via digital media and meet their health-related information needs.

Some of the caveats in the use and gratification approach are in order. The focus of this approach on individual intrinsic motivation leads to neglect of the social context that shapes people's attitudes and behaviors related to privacy. This is a particularly important point for people, given that the function of privacy in establishing one's stance relative to others always presupposes not only appropriate levels of privacy awareness, importance-attitude, confidence but also active negotiation of public-private boundaries in social interaction (Goffman, 1959). Combined, this leads to the need to explicate social conditions under which different features of privacy are related to the production of better health outcomes.

Recent studies in health care research, in particular, pointed out the importance of societal context as well as the role of trust in

health service. For instance, Kinlock et al. (2017) reported racial differences in the trust of hospitals and physicians, citing a low level of trust in medical care among African Americans compared to Whites. LaVeist, Isaac, and Williams (2009) also discovered that the mistrust among patients is also a critical predictor of the underutilization of health services, suggesting that the lack of health-related privacy capital (i.e., the lack of confidence or awareness) can lead to ineffective use of health services or even disengagement from digital media. Recent studies also raised the need to examine socioeconomic characteristics simultaneously with societal factors. For example, in a study by Thorpe et al. (2015), race disparities were ameliorated when African American and white men were living under similar social and environmental conditions. While these works did not directly address health privacy, the point is clear: health privacy as a capital creates incentive to seek out better engagement via digital media; and social variations may interact with demographic characteristics and significantly affect the equipment of health privacy capital, producing systematic disparities. As Eisen, Bowie, Gaskin, LaVeist, and Thorpe (2015) noted, more research is necessary to account for the confounding effects of race, socioeconomic status, and social conditions on the use of health service and health-related outcomes.

In this vein, social stratification perspectives (e.g., Coleman, 1990; Hollingshead & Redlich, 1958; Putnam, 2001) complement the uses and gratifications approach. Exercise of privacy does not occur in a vacuum but is deeply embedded in societal conditions. In particular, health norms and behaviors remain far from individual decisions but are instead anchored in the socialization process. Studies have repeatedly shown widening disparities among socio-demographic groups in their access to health resources (Rice & Katz, 2000; Veenstra, 2002) and emphasized the positive role of social capital (see Bolin, Lindgren, Lindström, & Nystedt, 2003) or social networks (such as family and friends) in enhancing the quality of health (Mohseni & Lindström, 2007; Wakefield & Poland, 2005). On one hand, the social divide derives from sociodemographics; on the other hand, we recognize the role of a network of friends and family in the efficacy of health-related decision making. Both point to the importance of societal resources that may harness the individual exercise of health privacy in its discrete roles.

#### 4. Research questions and hypotheses

In this work, we integrated the two approaches noted above and examined the concept of health privacy in these combined contexts. We examined the explicit functions of health privacy in (a) producing health-related digital interactions and (b) connecting to better health outcomes related to health service and confidence. Smith, Dinev, and Xu (2011) suggested adopting a comprehensive approach in studying information privacy and examined both antecedents and outcomes related to privacy concerns. Accordingly, when examining the consequences of health privacy in the quality of a healthy life, we first attended to discrete indicators of health privacy (awareness, importance-attitude, and confidence) and how various sociodemographic groups are equipped with different levels of health privacy capital.

**RQ1.** To what extent are people with different sociodemographic backgrounds and social capital equipped with health privacy capital in its key features (awareness, importance-attitude, and confidence)?

An initial hypothesis tested the role of health privacy in inducing mediated interaction with health professionals. Use of interactive digital media is a positive predictor of the effective exchange of health information (Huang, Chu, Lien, Hsiao, & Kao, 2009;

McCarroll et al., 2014). Consistent with the notion that health privacy capital is a set of individual assets that enable and motivate individuals to take full advantage of their benefits, we expected that the accumulation of health privacy capital would be positively related to the active use of digital channels in communication with health professionals:

**H1.** Those with higher levels of health privacy capital are more likely to have a higher level of digital interaction with health professionals.

Consistent with the first hypothesis, a second hypothesis predicted significant roles played by key features of health privacy capital in producing positive health outcomes related to perceived quality of health service and confidence in health maintenance.

**H2.** Those with higher levels of health privacy capital are more likely to have higher levels of perceived quality of health service and confidence in health maintenance

Finally, we tested the presence of interaction effects between health privacy capital and predictors of sociodemographics and social capital based on our explicit premise that key features of health privacy may remain anchored in societal contexts and social relationships. In other words, the respective societal predictors, when combined, may deepen differences in digital interactions and health outcomes related to perceived health service and confidence, conditioning the functions of health privacy. The effect of health privacy capital may be moderated by various aspects of societal contexts.

The present study posits that the interactive relationships will unmask nuanced roles of sociodemographics and social capital, unlike past studies that did not parse out the direct effects at the different levels of societal contexts. For instance, the existence of various attributes of social backgrounds, whether people are highly educated or financially well-off, leaves a possibility that the effect of any features of health privacy capital could depend on the functioning of societal characteristics (Bolin et al., 2003). Even socially well-connected people may be in a better position, to begin with, because their wider social networks can be a greater environment in which a large number of family and friends can accelerate the benefits of health privacy capital by providing support or compensating for the lack of health-related resources (Mohseni & Lindström, 2007; Wakefield & Poland, 2005). In this vein, one of the explicit premises in our analysis is that the combined effects from various societal contexts need to be carefully discerned, because health-related privacy and its behavioral effects are not only technological, but also socially determined. To summarize, all suggest that it is critical to differentiate societal contexts upon which the functions of health privacy capital will be conditioned.

**RQ2.** Will sociodemographic backgrounds and social capital indicators interact with health privacy capital?

#### 5. Method

##### 5.1. Sample

We analyzed secondary data from the Health Information National Trends Survey (HINTS, 2014), a nationally representative sample of adults (18 years or older) in the US ( $N = 3677$ ). The survey included questions about health behavior, digital media usage, attitudes and beliefs about health, and opinions about health topics like cancer. HINTS (2014) was a survey distributed by mail. A prepaid incentive of \$2 was offered to encourage participation. The respondents for the HINTS were recruited in two stages. In the first

stage, a stratified random sample of addresses was selected from a file of residential addresses. In the second stage, one adult was selected in each sampled household. The sampling frame consisted of a database of addresses used by Marketing Systems Group. Response rate for completed return was 26.3%. We analyzed data collected from August 20 to November 17, 2014. We were interested in those who owned any of the following mobile devices: smartphones, cell phones, or tablets. Interestingly, a majority of the sampled respondents (87.3%) had at least one of these mobile devices, indicating the ubiquity of mobile-based platforms (cell phones,  $n = 820$ ; tablets,  $n = 1587$ ; and smartphones,  $n = 2029$ ). We filtered out those who did not have any of those mobile devices ( $n = 334$ ) and missing responses ( $n = 131$ ).

Table 1 shows the demographic characteristics of this study's sample ( $n = 3212$ ), which closely matched those of the general population. However, in this study sample, the levels of income and age, on average, were slightly higher. We also had more white respondents, when compared to the U.S. census data (2010).

## 5.2. Measures

### 5.2.1. Health privacy capital

Health privacy was conceptualized in the key three features: (a) awareness, (b) importance-attitude, and (c) confidence. Awareness of privacy entails the presence or absence of overall knowledge about the collection of health information. It was measured with a single item: "As far as you know, do any of your doctors or other health care providers maintain your medical information in a computerized system?" Responses were made on a binary measure: 1 (*yes*) or 0 (*no*). For importance-attitude, respondents were asked to rate the importance of (a) the exchange of health data and (b) their own access to data with the following two statements: "Doctors and other healthcare providers should be able to share your medical information with one another electronically" and "You should be able to access your own medical information electronically." The response option was a 3-point scale ranging from 1 (*not at all important*) to 3 (*very important*). Confidence was measured with two questions that asked respondents to rate their level of confidence in health privacy on a scale from 1 (*not confident*) to 3 (*confident*): "How confident are you that safeguards (including the use of technology) are in place to protect your medical records from being seen by people who aren't authorized to see them?" and "How confident are you that you have some say in who is allowed to collect, use, and share your medical information?"

Health privacy items were factor-analyzed using principal components and direct oblimin rotation methods. This analysis demonstrated the three key features with no significant cross-loadings (factor loadings of 0.57 and 0.69 for importance-

**Table 1**  
Descriptive statistics for survey participants' sociodemographics and social capital index.

Characteristics	Smartphone-cell phone-tablet Users	General Population
Female (= 1)	0.59	0.51
Education	4.94	2.63 <sup>a</sup>
Age	53.48	46.69
Household Income	5.32	4.84
Nonwhite (= 1)	0.25	0.25 <sup>b</sup>
Social capital index	2.55	—
N	3212	3500

Notes. Cell entries are means. All data concerning the general population are based on Federal Communications Commission (FCC) Broadband Survey.

<sup>a</sup> Education in FCC Broadband Survey (2010) was measured in four categories.

<sup>b</sup> Nonwhite came from the 2010 U.S. census.

attitude; 0.78 and 0.74 for confidence with eigenvalues = 1.27 and 1.77, respectively). Awareness of health privacy, which consisted of a single item ( $M = 0.91$ ,  $SD = 0.27$ ), stood distinct from other items. The other two indicators, importance-attitude ( $M = 5.20$ ,  $SD = 1.02$ ;  $\alpha = 0.57$ ) and confidence ( $M = 4.00$ ,  $SD = 1.24$ ,  $\alpha = 0.74$ ), also remained distinctive. The significant yet relatively modest correlations among the three dimensions ( $r = 0.06$ ,  $p < 0.001$  between awareness and confidence;  $r = 0.10$ ,  $p < 0.001$  between awareness and importance-attitude;  $r = 0.14$ ,  $p < 0.001$  between importance-attitude and confidence) indicated that these privacy measures related to distinctive dimensions (Fig. 1). The same data set was used to run factor analysis and check the reliability. These two analyses are complementary because factor analysis is to detect the presence of an underlying dimension among variables, whereas Cronbach's alpha score provides insights on item reliability within each variable (see Chung, Park, Wang, Fulk, & McLaughlin, 2010).

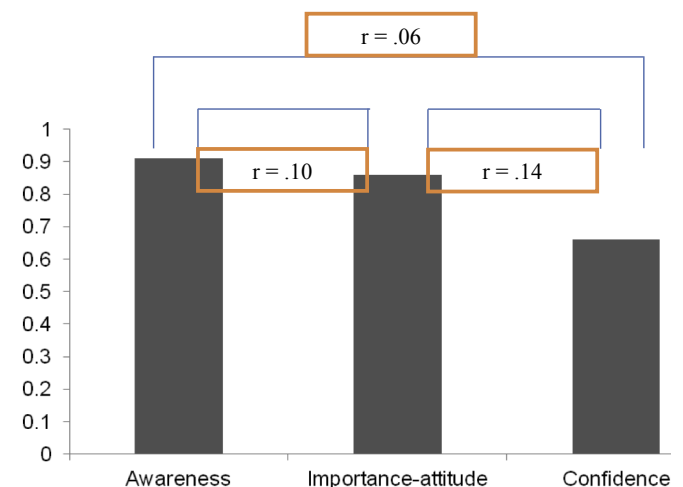
### 5.2.2. Social contextual variables

Two social contextual variables included (a) sociodemographics and (b) social capital variables. Five items (income, education, race, age, and gender) were used to assess the potential contextual influence of sociodemographic characteristics. For social capital indicators, we used the additive index of three measures to assess the presence of support networks of family and friends ( $M = 2.55$ ,  $SD = 0.81$ ,  $\alpha = 0.65$ ). Respondents were asked to indicate on a binary scale of 1 (*yes*) or 0 (*no*) whether anyone could help them with (a) emotional support, (b) health concerns, and (c) daily chores.

Education was measured on a 7-point scale of 1 (Less than 8 Years), 2 (8 through 11 years), 3 (years or completed high school), 4 (Post high school training other than college (vocational or technical)), 5 (Some college), 6 (College graduate), and 7 (Post-graduate). Household income was measured on a 9-point scale of 1 (\$0 to \$9999), 2 (\$10,000 to \$14,999), 3 (\$15,000 to \$19,999), 4 (\$20,000 to \$34,999), 5 (\$35,000 to \$49,999), 6 (\$50,000 to \$74,999), 7 (\$75,000 to \$99,999), 8 (\$100,000 to \$199,999) and 9 (200,000 and more). Gender and race were coded as binary (female = 1; white = 1) and age was the actual number. Missing values were deleted (list-wise) from analysis.

### 5.2.3. Covariate

Chronic health issues influence patterns of the use of health information as well as perceived quality of health service and



**Fig. 1.** Bivariate correlations between different features of health privacy capital and average scores. Notes. All features were converted into ratio (0–1) for visual comparison. Bivariate correlations ( $r$ ) were all significant at  $p < 0.001$ .



confidence in health maintenance (Angst & Agarwal, 2009). Individuals with chronic health issues are more likely to seek information, thereby resulting in more opportunities for potential interaction and benefits (Lafky & Horan, 2011). Thus, in our analysis controlling for chronic health conditions was necessary. Those who reported having one or more of the following conditions (diabetes, high blood, heart attack/condition, chronic lung disease, arthritis, or depression–anxiety) was coded as 1 (*having a chronic health issue*), whereas those who reported having none of these problems were coded as 0 (*not having any chronic health issue*) ( $M = 1.34$ ,  $SD = 1.33$ ).

#### 5.2.4. Criterion variables

Three criterion measures were (a) digital interaction with health professionals, (b) perceived quality of health service, and (c) confidence in health maintenance. Each of these measures has been considered a crucial determiner in assessing the effectiveness of the mediated health environment analyzed for this study (e.g., Ferguson, 1998). Digital interaction with health professionals was measured with six items. Respondents were asked on a binary scale, 1 (*yes*) or 0 (*no*), whether they had participated in the following modes of interaction in the past year: email, text, social media, smartphone–mobile apps, video conferencing, and fax. We created a six-item additive index ( $M = 1.16$ ,  $SD = 0.55$ ,  $\alpha = 0.55$ ). For perceived quality of health service, two questions were asked: “How often did you feel you could rely on your doctors, nurses, or other health care professional in the past 12 months?”; “Overall, how would you rate the quality of health care you received in the past 12 months?” Respondents were asked to report on a scale, ranging from 0 (*never*) to 4 (*always*). A two-item additive index was created ( $M = 6.49$ ,  $SD = 1.44$ ;  $\alpha = 0.80$ ). For health maintenance confidence, individuals were asked how confident they were about their ability to take good care of their health; they responded on a scale anchored by 1 (*not confident at all*) and 5 (*completely confident*) ( $M = 3.81$ ,  $SD = 0.84$ ).

## 6. Results

For RQ1, in order to examine the relationship between the five indicators of sociodemographics and the facets of health privacy capital—awareness, importance-attitude, and confidence—a series of regression analyses was conducted. For the binary measure of awareness, we carried out logistic regression. Logistic regression assumes the linearity of independent variables. That is, the independent variables are linearly related to each level of categorical (dependent) variable, expressed in the odds ratio (maximum likelihood estimate). Because maximum likelihood estimates are less powerful than ordinary least squares, logistic regression is suitable for the analysis of a large sample size such as this study. For the continuous measures of importance-attitude and confidence, we conducted ordinary least squares (OLS) regression.

Overall, sociodemographic patterns were found to be significant, related to each dimension of health privacy capital (Table 2). First, the level of education remained the most consistent predictor in all three dimensions with a higher level of education associated with higher levels of health privacy capital (odds ratio = 1.18,  $\beta = 0.07$ ,  $p < 0.01$ ,  $\beta = 0.08$ ,  $p < 0.001$ ). Second, those with higher levels of income ( $\beta = 0.11$ ,  $\beta = 0.10$ ,  $p < 0.001$ , for confidence and importance-attitude) were found to have more health privacy capital. Third, the dimensions of awareness and confidence were also related to the social capital index (odds ratio = 1.30,  $p < 0.01$ ,  $\beta = 0.16$ ,  $p < 0.001$ , respectively). Among demographic variables, females and older people were more likely to be aware of health information privacy (odds ratio = 1.73,  $p < 0.001$ , odds ratio = 1.02,  $p < 0.001$ ). We also found that older people had less confidence in

**Table 2**

Regression (OLS and logistic) analysis examining the impact of social contextual variables on health privacy capital ( $n = 3212$ ).

	Health privacy capital		
	Awareness	Importance-attitude	Confidence
	Odds ratio	$\beta$	$\beta$
Intercept	–0.60	4.75	3.07
Female (= 1)	1.73*** (0.15)	0.01 (0.04)	0.02 (0.03)
Age	1.02*** (0.00)	–0.01 (0.00)	–0.05* (0.00)
Education	1.18** (0.05)	0.08*** (0.01)	0.07*** (0.01)
Household income	1.02 (0.03)	0.10*** (0.01)	0.11*** (0.00)
Nonwhite (= 1)	0.89 (0.17)	0.00 (0.04)	0.02 (0.03)
Social capital index	1.30** (0.08)	0.00 (0.02)	0.16*** (0.02)
R Square	0.055 <sup>a</sup>	0.026	0.068

Notes. Ordinary least squares (OLS) linear regression (for importance-attitude and confidence) and logistic regression analyses (for awareness) were run. Cell entries are odds ratio from logistic regression and standardized regression coefficients ( $\beta$ ) from OLS. Ratio higher than 1 indicates higher odds, with ratio lower than 1 for lower odds of outcome.

Entry in parentheses are standard errors.

\* $p < 0.05$ . \*\* $p < 0.01$ . \*\*\* $p < 0.001$ .

<sup>a</sup> Nagelkerke R Square is reported for logistic regression.

privacy, although the size of coefficient suggests a relatively weak association between age and privacy confidence ( $\beta = -0.05$ ,  $p < 0.05$ ). None of the dimensions was significantly related to race.

For H1 and H2, separate hierarchical regression analyses were conducted for each dimension of health privacy capital (Table 3). Overall, the findings revealed robust support for both hypotheses. All three dimensions of health privacy capital were significant in predicting criterion variables, holding constant social contextual variables and chronic health conditions. That is, those with higher levels of health privacy capital were more likely to report higher levels of digital interaction with health professionals ( $\beta = 0.04$ ,  $p < 0.05$  for awareness;  $\beta = 0.07$ ,  $p < 0.001$  for importance-attitude;  $\beta = 0.06$ ,  $p < 0.01$  for confidence) (H1). They also reported higher levels of perceived quality of health service ( $\beta = 0.04$ ,  $p < 0.05$ ;  $\beta = 0.06$ ,  $p < 0.01$ ;  $\beta = 0.27$ ,  $p < 0.001$ ) and health confidence ( $\beta = 0.05$ ,  $p < 0.01$ ,  $\beta = 0.03$ ,  $p < 0.10$ ;  $\beta = 0.15$ ,  $p < 0.001$ ) (H2).

Although the direct effects of health privacy capital were the main interest of our analysis, showing how each of the three criterion variables was embedded in societal conditions gives us understandings of nuanced functions of health privacy capital. In addition, the relatively weak or modest sizes of coefficients in the direct relationships raise a possibility that there are potential interactions that mask the distinct role of health privacy capital at different levels of social contexts. The upper row in Table 3 shows the predictive power of social contextual variables as a block (incremental  $R^2 = 0.021$ , 0.050, and 0.068). The impact of age remained consistent as the hierarchical analysis provided significance for all three measures ( $\beta = -0.05$ ,  $p < 0.01$ ;  $\beta = 0.12$ ,  $p < 0.001$ ;  $\beta = 0.12$ ,  $p < 0.01$ ). Similarly, those with higher levels of income were found consistently better in health outcomes ( $\beta = 0.06$ ,  $p < 0.05$ ;  $\beta = 0.11$ ,  $p < 0.001$ ), and they tended to be more actively engaged in digital interaction with health professionals ( $\beta = 0.05$ ,  $p < 0.05$ ). In this regard, the effect of education was positive in digital interaction and health confidence ( $\beta = 0.09$ ,  $p < 0.001$ ;  $\beta = 0.07$ ,  $p < 0.01$ ) but not in perceived quality of health service. The positive and sizable impacts of the social capital index were also clear in quality of health service and health confidence ( $\beta = 0.16$ ,  $p < 0.001$ ;  $\beta = 0.16$ ,  $p < 0.001$ ), but it did not necessarily affect the level of digital interaction.

To examine RQ2, we investigated the interactive relationships between social contextual variables and measures of health privacy capital (see Table 4). For quality of health service and confidence in health maintenance, education interacted with health privacy

**Table 3**  
Hierarchical regression analysis examining the impact of health privacy capital on digital interaction and health outcomes (n = 3212).

	Digital interaction	Health outcomes	
	$\beta$	Perceived health service quality $\beta$	Healthmaintenance confidence $\beta$
Intercept	1.018	4.679	3.067
Female (= 1)	0.01(0.02)	0.00(0.06)	0.02(0.03)
Age	-0.05***(0.00)	0.12***(0.00)	-0.05***(0.00)
Education	0.09*** (0.00)	0.04(0.02)	0.07** (0.00)
Household income	0.05*(0.00)	0.06** (0.01)	0.11*** (0.00)
Nonwhite (= 1)	0.02(0.02)	0.00(0.07)	0.02(0.03)
Social capital index	-0.00(0.01)	0.16*** (0.03)	0.16*** (0.02)
<i>R Square</i>	0.021	0.050	0.068
Chronic health issue	0.05*(0.02)	-0.01(0.02)	-0.21*** (0.01)
<i>R Square</i>	0.023	0.050	0.104
Health privacy capital			
Awareness	0.03*(0.03)	0.04*(0.14)	0.05** (0.06)
<i>R Square</i>	0.024	0.052	0.106
Importance-attitude	0.07*** (0.01)	0.06** (0.03)	0.03*(0.01)
<i>R Square</i>	0.029	0.055	0.107
Confidence	0.06***(0.00)	0.27*** (0.02)	0.15*** (0.01)
<i>R Square</i>	0.027	0.126	0.125

Notes. Entry in parentheses are standard errors. Separate OLS regression analyses were run for the criterion variables, with blocks of independent variables (social contextual variables, chronic health issue, and each of privacy capital dimensions) entered in each step.  
† $p < 0.10$ . \* $p < 0.05$ . \*\* $p < 0.01$ . \*\*\* $p < 0.001$ .

**Table 4**  
Interactive relationships between social contextual variables and health privacy capital.

	Digital interaction	Health outcomes	
	$\beta$	Perceived health service quality $\beta$	Healthmaintenance confidence $\beta$
Awareness			
X Gender	-0.011 (0.01)	0.007 (0.04)	0.032 (0.01)
X Income	0.019 (0.01)	0.014 (0.04)	0.029 (0.02)
X Nonwhite	0.012 (0.01)	0.004 (0.04)	-0.015 (0.01)
X Age	-0.013 (0.01)	0.012 (0.04)	0.008 (0.01)
X Education	0.016 (0.01)	-0.010 (0.04)	-0.021 (0.01)
X Social capital	-0.004 (0.01)	-0.046*(0.03)	-0.026 (0.01)
<i>R Square</i>	0.026	0.054	0.108
Importance-attitude			
X Gender	-0.002 (0.01)	-0.072** (0.03)	-0.012 (0.01)
X Income	-0.006 (0.01)	-0.039 (0.03)	0.009 (0.01)
X Nonwhite	0.001 (0.01)	0.048*(0.03)	0.003 (0.01)
X Age	-0.010 (0.01)	0.005 (0.03)	-0.006 (0.01)
X Edu	0.035 (0.01)	-0.018 (0.03)	-0.012 (0.01)
X Social capital	-0.003 (0.01)	-0.005 (0.03)	-0.008 (0.01)
<i>R Square</i>	0.030	0.064	0.107
Confidence			
X Gender	-0.010 (0.01)	-0.007 (0.03)	0.023 (0.01)
X Income	0.000 (0.01)	0.018 (0.03)	-0.005 (0.01)
X Nonwhite	0.034 (0.01)	0.028 (0.03)	0.012 (0.01)
X Age	-0.010 (0.01)	-0.015 (0.03)	-0.001 (0.01)
X Education	0.039 (0.01)	-0.073** (0.03)	-0.076*** (0.01)
X Social capital	-0.017 (0.01)	-0.024 (0.03)	-0.015 (0.01)
<i>R Square</i>	0.030	0.132	0.133

Notes. Entry in parentheses are standard errors. Interactions were the final blocks in each regression equation. Separate OLS regression analyses were run for all criterion variables, with blocks of independent variables (social contextual variables, chronic health issue, and each of privacy capital dimensions) entered in each step.  
† $p < .05$ . \*\* $p < .01$ . \*\*\* $p < .001$ .

confidence, albeit relatively weak interaction terms ( $\beta = -0.07$ ,  $p < 0.01$ ;  $\beta = -0.07$ ,  $p < 0.001$ , respectively). Interactions between importance-attitude and gender ( $\beta = -0.07$ ,  $p < 0.01$ ) and between importance-attitude and nonwhite ethnicity ( $\beta = 0.04$ ,  $p < 0.01$ ) were also significant for perceived quality of health service. Regarding social capital, an interaction effect was significant for perceived quality of health service ( $\beta = -0.04$ ,  $p < 0.01$ ) but not for other criterion variables. Fig. 2 shows the consistent pattern of interaction effects of health privacy confidence in affecting quality of health service and confidence in health maintenance.

## 7. Discussion

### 7.1. Summary of main results

Our aim was to examine the impact of health privacy capital on the use of health-related digital technologies as well as on individuals' perception of quality of health service and confidence in maintaining good health. The focus was on the health privacy as a significant capital resource, with particular attention to the way social contexts relate to individual capacities to understand (awareness) and evaluate the importance of health information privacy (importance-attitude) and to feel confident in the use of measures designed to protect health information privacy (confidence). We draw upon various strands of (a) uses and gratifications (e.g., Blumler & Katz, 1974; Katz & Rubin, 1981) and (b) social stratification (e.g., Bolin et al., 2003; Coleman, 1990; Mohseni & Lindström, 2007; Putnam, 2001; Rice & Katz, 2000; Veenstra, 2002), advancing the notion of health privacy as sociotechnical capital. From this premise, the effect of health privacy capital was tested, taking into account its multifaceted nature and social contexts. We included nuanced measures of health privacy capital in three dimensions. Interactions between each dimension and social contextual variables were also observed.

The findings lent credence to the view that health privacy capital is a multifaceted sociotechnical asset (cf. Hong & Thong, 2013; Kenny & Connolly, 2015; Resnick, 2002, pp. 84–87; Uslaner, 2004). The results of factor analysis showed that health privacy consisted with related but distinctive dimensions and identified the three key dimensions of health privacy: (a) awareness, that is, knowing the issues involved with health information privacy; (b) importance-attitude, that is, understanding the importance of accessing and exchanging private health information via electronic means; and (c) confidence, that is, feeling confident in one's ability to protect private health information. Our results also show that populations in different social contexts as measured by sociodemographic and social capital indicators are equipped with different levels of health privacy capital.

Extant research on privacy (Aquisti & Gross, 2006; Fogel & Nehmad, 2009; Litt, 2013; Park, 2015, 2017; Park & Jang, 2014; Walrave, Vanwesenbeeck, & Heirman, 2012) has shown persistent gaps among people with varying demographic backgrounds; those gaps occur in awareness of privacy, concern, and willingness to provide personal data. The findings of this study confirm the persistent disparities among different sociodemographic segments in the privacy domain, particularly related to health information (Appari & Johnson, 2010; Chin et al., 2012; Park et al., 2012). Results also suggest that social networks such as friends or family members can be critical resources in developing health privacy capital because more social capital was associated with a higher level of privacy capital. Collectively, the findings are in line with prior studies (e.g., Cattell, 2001; Wakefield & Poland, 2005) that showed the practice of social capital building and friendships was significantly linked to better health.

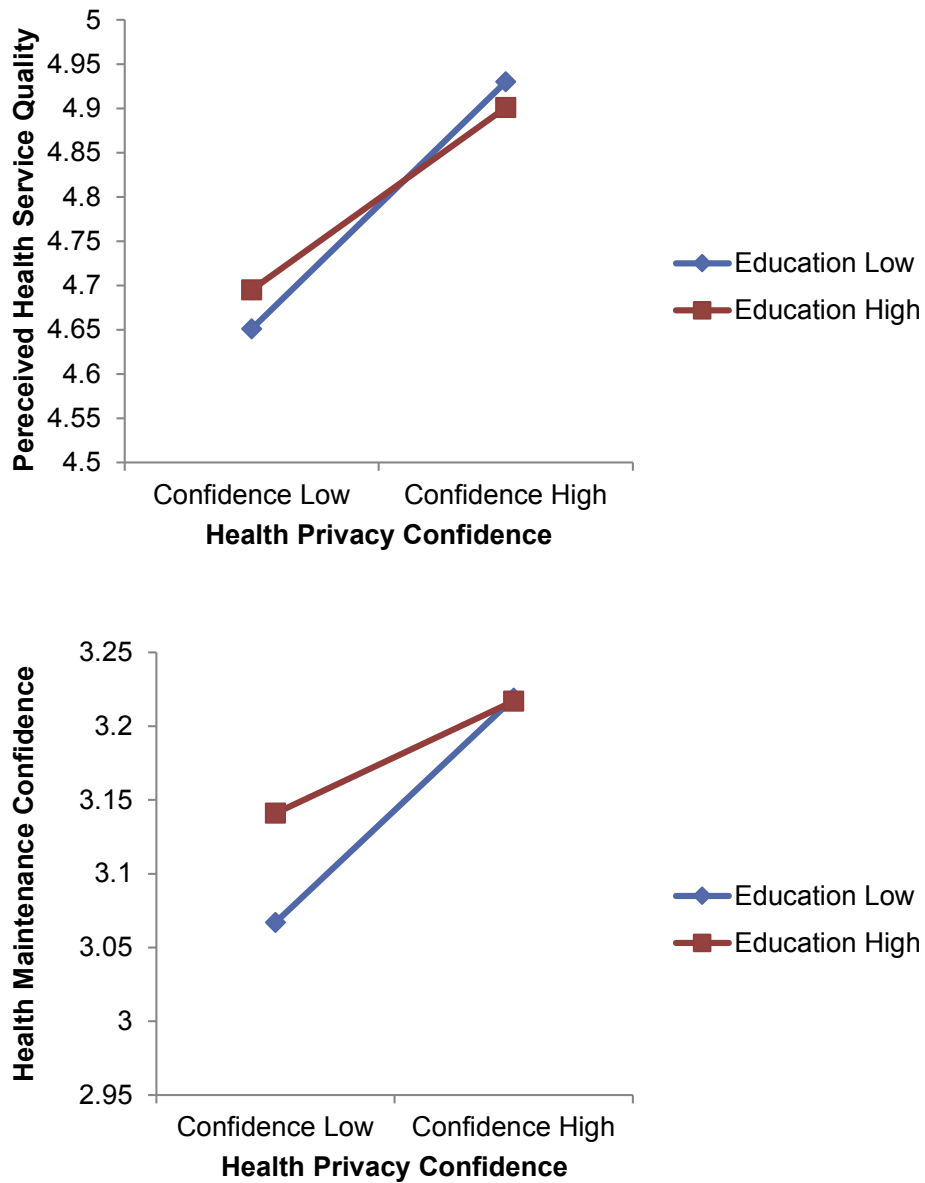


Fig. 2. Interaction effects between education and health privacy confidence. Note. We assigned 1 and 0 in each of the four groups (high and low) in the final regression equations.

Given that the sample analyzed for the current study comprised users of cell phones, smartphones, and tablets with ubiquitous mobile platform experience, the disparities based on sociodemographic characteristics were surprising. In other words, users who were readily exposed to digitally enriched mobile devices seem equally susceptible, for instance, to variations that leave behind those with a lower level of education. Similarly, the finding concerning income suggests that a higher income is conducive to the accumulation of health privacy capital, but a lower income is not. Age also raises a concern because older people, even when equipped with mobile devices, remained less confident in health privacy than younger people. Given the important function of privacy capital, we were surprised to observe the extent of variations based on sociodemographics with regard to individual capacities to understand (awareness of privacy), evaluate (attitude toward the importance of privacy and data sharing), and be confident (confidence in the possibility of maintaining privacy) in health-related personal information.

More specifically awareness of health privacy varied by gender,

age, and education. Women compared to men reported that they were much more likely to be aware of health privacy issues. Older respondents also reported being more aware of health privacy issues and yet showed less confidence in maintaining health privacy. This finding calls for the need to provide training for older population about the availability and use of privacy management tools when it comes to the use of digital health information or resources. Such training can be particularly valuable for aging population who often deals with deteriorating health of their own and family members. Education influenced all three facets of health privacy capital. The more educated, compared to the less educated, were more aware of health-related privacy issues as well as their importance at the same time more positive about their capacity to use privacy tools. As digital health access is critical to empowerment, health education and communication need to focus on better equipping people to understand issues and develop skills related to health privacy management, particularly among those with less formal education and less income.

Another notable point is the support for the hypothesized

effects of health privacy capital on (a) digital interaction with health professionals and (b) health outcomes defined as perceived quality of health service and confidence in health maintenance. In sum, the main thesis was robust: We showed that different facets of health privacy capital can be critical determinants for individuals' interaction with health professionals in their use of digital technologies and ultimate positive health outcomes (McMullan, 2006). The consistent and direct function of health privacy capital in engaging in more active digital interaction and producing the better health outcomes are noteworthy. Simply put, privacy matters in inducing more active communication with health professionals, while positively affecting overall health outcomes.

### 7.2. Interaction effects

Still, interactive relationships show that the effects of health privacy capital were conditional upon social contexts. For example, interactions between education and health privacy confidence were significant in both dimensions of health outcomes (Fig. 2). Findings suggested that a certain type of privacy confidence compensates for lack of education by (a) encouraging interaction with health professionals via digital platforms and (b) promoting trust in health service as well as confidence. In this vein, the interaction between privacy awareness and the social capital index provides an additional insight. We found that those with a low level of networking with family and friends still benefit from a high level of privacy awareness, whereas those without adequate awareness cannot benefit when they remain poorly networked. Put differently, privacy awareness as a predictor seems to play an enabling role for those who lack basic social networks because it helps them fully trust and efficiently navigate the health system to their benefit.

Overall, our study supports the importance of examining individual motives and perceptions as well as the need to understand social contexts. On one hand, our study findings identify the function of individual motives (Blumler & Katz, 1974; Rubin, 1981) (a) in seeking out active engagement via health-related digital interaction and (b) in better connecting to health service and enhancing overall health confidence. On the other hand, results show how people's awareness of privacy, attitude toward the importance of privacy and data sharing, and confidence in the ability to maintain privacy are subtly embedded in social conditions with the exercise of privacy not occurring in a contextual vacuum (Park, 2015; Park & Jang, 2014, 2016; Rice & Katz, 2000; Veenstra, 2002).

### 7.3. Implications

Two practical lessons have emerged. First, given the significant roles played by all facets of health privacy capital, health professionals should make a focused effort to increase not only awareness but also confidence and the right attitude toward evaluating the importance of the flow of health data. This effort will eventually bring about a positive change and help the public engage more actively with the health system. The sharing of and access to health information can increase when people trust the system, have motivation and a willingness to share, and understand safeguards (Pickarda & Swanb, 2015). Second, healthcare providers and those concerned about health privacy should not treat medical data as property to give up in a zero-sum game. Instead, privacy should be considered an asset upon which to build tangible health-related benefits. Collectively, this also indicates that perceived quality of health service and trust may not be strictly about medical service per se. Instead, what appears a critical determinant is the context in which information is used, shared, and appropriated and more importantly, the way the patients see the importance of data

sharing, feel confident that they can control their records, and understand overall contexts of the use of medical data.

On a theoretical note, we suggest a useful framework in identifying distinctive key features in conjunction with differences in individual needs and social positions while situating privacy as capital in the context of health. From our findings, it is clear that there are discernable effects of health privacy capital as multifaceted assets. In this scenario, individual capabilities to manage and understand the flow of data, to evaluate the importance of personal data sharing, and to be confident about protecting one's data are assets needed to communicate and interact with health professionals and create positive health benefits.

## 8. Conclusion and future directions

Because we relied on a national sample, the findings from our study can make unique contributions to advancing health privacy as a capital and understanding its positive roles. Nevertheless, the cross-sectional nature of the survey data did not allow us to ascertain causality. In this vein, a longitudinal panel study with the inclusion of more reliable measures will establish causal claims. In addition, analytically, the precise mechanism under which socio-demographics affect the acquisition of health privacy capital remains unknown under our analysis. In this respect, we post-hoc analyzed the roles of different races/ethnicities because the binary category (non-whites) in our main analyses may have obscured subtle differences within minorities (see Appendix: Table A.1). We observed that, compared to the whites, the level of privacy awareness among Hispanics and Asian/Pacific islanders was significantly low. We also saw a statistically significant but marginal relationship between those of Hispanic origin and perceived health service quality, indicating that Hispanics among minority groups may get behind in acquiring quality health outcomes.

Findings on sociodemographics pointed to the general trend and the deep-rooted causes. Here we see the utility of conducting focus group studies, which potentially allow us to discover other societal barriers hindering minority populations. For instance, we might be able to probe deeper into another puzzling finding that African Americans did not enjoy positive health outcomes despite their active use of digital channels for health service (again, compared to the whites). Focus group studies can offer an insight on how possessing a high level of health privacy capital in each dimension may be potentially linked to different types of health outcomes among African Americans, differently from other populations.

An investigation into the patients with a specific illness (such as cancer) will offer further insights on how those with similar sociodemographics and medical conditions tend to develop health privacy capital and manage privacy concern. Finally, a fruitful line of future research can involve the use of a different methodology that might help us discern other important facets of privacy. For example, so-called "big data," such as real-time frequency as well as the duration of digital interaction (e.g., Chung, 2015), can provide a more complete picture that captures realistic settings in which the key features of privacy operate in the context of health-related data.

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### Appendix



**Table A.1**  
Regression analyses examining the roles of different races/ethnicities

	Health privacy capital			Digital interaction	Health outcomes	
	Awareness	Importance-attitude	Confidence		Perceived health service quality	Healthmaintenance confidence
	Odds ratio	$\beta$	$\beta$	$\beta$	$\beta$	$\beta$
Intercept	–0.22	4.78	3.07	0.98	4.79	3.07
Black	0.98(0.20)	0.02(0.05)	0.03(0.04)	0.05 <sup>*</sup> (0.02)	0.02(0.08)	0.03(0.04)
Hispanic	0.49 <sup>***</sup> (0.18)	–0.03(0.05)	–0.01(0.04)	0.03(0.02)	–0.06 <sup>**</sup> (0.09)	–0.01(0.04)
Asian/Pacific Islander	0.51 <sup>*</sup> (0.30)	–0.03(0.09)	–0.03(0.07)	–0.00(0.05)	–0.03(0.17)	–0.03(0.07)
Native American	1.95(0.52)	–0.02(0.11)	–0.01(0.09)	0.00(0.06)	–0.01(0.18)	–0.01(0.09)
R Square	0.074 <sup>a</sup>	0.029	0.071	0.024	0.058	0.071

Notes. Only race/ethnicity variables are shown. Social contextual variables as in Tables 2 and 3 were entered in separate regression analyses. White, non-Hispanic was the reference category (for comparison).

<sup>\*</sup> $p < 0.05$ . <sup>\*\*</sup> $p < 0.01$ . <sup>\*\*\*</sup> $p < 0.001$ .

<sup>a</sup> Nagelkerke R Square is reported for awareness.

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