Drivers of Health Information Privacy Concern: A Comparison Study

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Abstract

There has been an exponential increase in the utilization of health ICTs by both health professionals and individual citizens. Despite the many benefits these technologies offer, citizens’ health information privacy concerns are commonly cited as a barrier to their sustained growth. In order to address these concerns and ensure the continued success of health ICTs, the factors driving concern must be understood. At present there is a lack of understanding of what factors can affect citizens’ health information privacy concerns (HIPC). This paper addresses this gap in our knowledge by developing and testing a framework which examines the antecedents to HIPC. The findings indicate that individual characteristics such as age, individual perceptions such as perceived sensitivity, and individual experiences can all influence health information privacy concerns. This paper represents an important initial step in unraveling the role the labyrinthine privacy construct plays in the health context.

Keywords

Health information privacy, antecedents, information boundary theory, protection motivation theory.

Introduction

In recent years, there has been exponential increase in the adoption of Health Information and Communication technologies (ICTs), by health organizations and citizens. ICTs implemented by health organizations include e-scheduling systems, e-prescribing systems, and Electronic health record systems (EHRs). MHealth can be described as the utilization of mobile technologies to realize health objectives and includes mHealth applications (WHO, 2011). These applications enable individuals to personally monitor a range of health issues from chronic illness to fitness. The adoption of health ICTs by both health organizations and citizens can lead to the realization of many benefits. For instance, EHRs can result in efficiencies in health service delivery and reduce data duplication (Angst, 2006). mHealth solutions present individuals with chronic diseases with the opportunity to manage their disease, and encourage other individuals to adopt healthy behaviors (Eng & Lee, 2013). Both EHRs and mHealth technologies enable the sharing of vast quantities of health data among many parties. For example, a study of 12 mHealth applications revealed that user data was shared with 76 third parties (FTC, 2014). Unsurprisingly many argue that citizens’ health information privacy concerns represent a barrier to the growth of health ICTs (Chhanabhai & Holt, 2007). Indeed, research shows that privacy concerns reduce citizens’ acceptance of EHRs, and adoption of personal health records (Angst & Agarwal, 2009; Li et al., 2014). Due to their nascence, the relationship between privacy concerns and mHealth application adoption has not been examined. In order to ensure the future success of health ICTs, citizens’ health information privacy concerns must be understood and addressed. There is a dearth of research which focuses on testing the drivers of citizens’ health information privacy concerns. This paper addresses this gap in our understanding.
Literature Review

The information privacy literature was reviewed to identify the antecedents relevant to the health context and choose a measure of privacy concern suitable to this context. Information privacy has attracted investigation from various academic disciplines. Due to the varying perspectives from which the privacy is examined, a host of definitions have emerged. One widely used definition describes privacy as controlling access to information about oneself (Westin, 1967). The majority of privacy studies in Medical Informatics journals fail to adequately differentiate information privacy from similar but distinct concepts, such as security and confidentiality (Shaw et al., 2011). In the MIS literature, information privacy is defined as individuals' desire to control how their personal information is collected and used (Bélanger & Crossler, 2011). This definition represents a comprehensive attempt to explain privacy and acknowledges that individuals cannot fully control their information, but they desire greater control. Thus, this definition is adapted to the health context, with information privacy described as individuals' desire to be afforded greater control over how their health information is collected and disseminated (Kenny and Connolly, 2015). In terms of examining privacy concerns, the MIS literature offers a number of validated measures. In the medical informatics literature in contrast, many studies measure privacy with one item such as ‘Are you concerned for the confidentiality and privacy of your health records?’ (Chhanabhai & Holt, 2007). While confidentiality and privacy are both interesting concepts, the inclusion of both concepts within one question obfuscates our understanding. As a result, it is necessary to adapt a measure from the MIS literature. Within this field, the Concern for Information Privacy measure, CFIP (Smith et al., 1996) and the Internet Users’ Concern for Information Privacy measure, IUIPC (Malhotra et al., 2004) have both been retested in a host of studies (Bélanger & Crossler, 2011). CFIP consists of four dimensions; collection, unauthorized secondary usage, improper access, and errors, while IUIPC is comprised of three dimensions; collection, control, and awareness. More recently, Hong and Thong (2013) combined the CFIP and IUIPC measures to create the Internet Privacy Concerns measure (IPC). IPC is arguably the most comprehensive measure as it includes the six most popular dimensions in the existing literature. To date, a small number of studies have utilized CFIP in the health context (Angst & Agarwal, 2009; Li et al., 2014; Dinev et al., 2016). This paper argues that IPC represents an ideal measure of privacy concerns in the health context for two reasons. First, the wording of the IPC items captures concerns regarding what organizations ‘should do or not do’ (Hong & Thong, 2013). Second, it is argued that all six dimensions are pertinent to the health context, especially control and awareness which are not included in CFIP. Thus IPC is adapted and termed HIPC (health information privacy concerns). Each dimension is justified in table 1 below.

<table>
<thead>
<tr>
<th>Dimension</th>
<th>HIPC Definition</th>
<th>Relevance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Collection</td>
<td>An individual’s concern regarding the collection and storage of large quantities of their health data.</td>
<td>Studies show that individuals are concerned regarding the electronic collection and storage of their health data (eg. Flynn et al. 2003)</td>
</tr>
<tr>
<td>Unauthorized</td>
<td>Unauthorized Secondary Use</td>
<td></td>
</tr>
<tr>
<td>Use</td>
<td>An individual’s concern that their health data collected for one purpose, is used for another purpose without their permission.</td>
<td>Studies show that there are a host of potential uses for health data such as marketing. If individuals believe these potential uses may occur, they are likely to express concerns.</td>
</tr>
<tr>
<td>Improper Access</td>
<td>An individual’s concern that an organization cannot prevent unauthorized individuals from accessing their personal health data.</td>
<td>Studies show that individuals are concerned regarding potential access to their health data by parties such as employers and legal companies (eg. Powell et al., 2006).</td>
</tr>
<tr>
<td>Errors</td>
<td>An individual’s concern that organizations do not have measures in place to prevent and correct errors</td>
<td>Studies show that individuals believe the digitization of health data can generate more errors (Westin, 2005).</td>
</tr>
<tr>
<td>Control</td>
<td>Individuals’ concern that they cannot control their health data.</td>
<td>Individuals desire granular control over their health data (Caine &amp; Hanania, 2013).</td>
</tr>
<tr>
<td>Awareness</td>
<td>An individual’s concern that they lack awareness of how their health data is used and protected.</td>
<td>It has been highlighted that individuals are not aware of how their health data is used (Angst, 2006). This is likely to influence concerns.</td>
</tr>
</tbody>
</table>

Table 1. Dimensions of HIPC
Identifying the Antecedents

Among the myriad of information privacy studies, a large number of potential antecedents have been examined. It is widely accepted that the influential antecedents will be largely determined by the context of the study (Smith et al., 2011). The few existing health privacy studies include a small number of antecedents. This paper tests a broader set of antecedents deemed pertinent to the health context. In an effort to bring some clarity to the literature, Li (2011) categorized all previously examined antecedents. Table 2 below reviews these antecedents to identify which factors are pertinent to the health context.

Table 2. Antecedents to HIPC

<table>
<thead>
<tr>
<th>Factor</th>
<th>Findings (MIS)</th>
<th>Findings (Health)</th>
<th>Justification</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gender</td>
<td>Females consistently express higher privacy concerns (Joinson et al. 2010)</td>
<td>Females express higher health privacy concerns (Larie et al. 2009)</td>
<td>Included. Evidence supports the influence of gender on privacy concern.</td>
</tr>
<tr>
<td>Age</td>
<td>Age positively influences concern (Joinson et al. 2010).</td>
<td>Health privacy concerns increase with age (Larie et al. 2009).</td>
<td>Included. Numerous studies support the influence of age on concern.</td>
</tr>
<tr>
<td>Experience of privacy invasion</td>
<td>Examined in few studies but consistently found to increase concern (Smith et al. 1996).</td>
<td>Health privacy invasion increases concern (Bansal et al. 2010)</td>
<td>Included. Influence of privacy invasion supported in various contexts including health.</td>
</tr>
<tr>
<td>Risk beliefs</td>
<td>Risk beliefs increase concern (Hong &amp; Thong 2013).</td>
<td>Not examined as an antecedent to date.</td>
<td>Included. It is argued that risk will influence privacy concerns</td>
</tr>
<tr>
<td>Trust beliefs</td>
<td>Trust beliefs have been found to reduce privacy concern (Hong &amp; Thong 2013).</td>
<td>Trust in EHRs reduces concern (Dinev et al. 2016)</td>
<td>Included. Support provided in various contexts.</td>
</tr>
<tr>
<td>Perceived Sensitivity</td>
<td>Individuals express higher concerns for data they view as sensitive (Ward et al. 2005).</td>
<td>Perceived sensitivity increases concern (Bansal et al. 2010).</td>
<td>Included. Perceptions of sensitivity are likely to increase concern.</td>
</tr>
<tr>
<td>Awareness of privacy media coverage</td>
<td>Awareness of privacy news increases privacy concerns (Smith et al. 1996).</td>
<td>Not examined to date.</td>
<td>Included. Supported in other contexts.</td>
</tr>
</tbody>
</table>

Theoretical Background

Previous information privacy studies have utilized a number of theories to explain the factors influencing information privacy concern (Li, 2012). This paper extends two theories to the health context. Firstly, the Information boundary theory is utilized to explain the link between perceived sensitivity and HIPC. Information boundary theory states that individuals create boundaries to determine what information they are prepared to disclose (Petronio, 1991). If individuals perceive information to be sensitive, they are less likely to be comfortable with its disclosure. It is thus argued that individuals’ perceptions regarding the sensitivity of their health data will influence their HIPC. Secondly, protection motivation theory (PMT) is harnessed. PMT is comprised of two broad components. Firstly, the threat appraisal includes individuals’ perceptions of the threats facing their information, their severity and the likelihood these threats will occur (Rogers, 1975). Three potential antecedents form the individual’s threat appraisal. Firstly, awareness of privacy media coverage is described as individuals’ perception of the risks facing their health information. If individuals are aware of media coverage which reports the misuse of data, they are more cognizant of the risks to their data. Previous experience of privacy invasion also represents individuals’ perceptions of the risks to their information. If an individual believes their information has been previously invaded, they are aware this may occur again. Lastly, individuals’ perceived risk represents their assessment of the likelihood these perceived threats will occur. Risk is examined as individuals’ perception of the risk that disclosing their information to health professionals or technology vendors will result in negative outcomes. Coping appraisal is represented by trust beliefs. If individuals’ trust health professionals, and technology vendors to protect their data, they will express lower HIPC.
Proposed Model & Hypotheses

Following the preceding discussion, a number of hypotheses related to individuals' characteristics, perceptions, and experiences are presented. This study follows on from a previous paper (Kenny & Connolly, 2015) and tests many of the antecedents discussed in this paper.

**Individual Characteristics**

Studies have shown that gender influences individuals' information privacy concerns, with females expressing higher concerns in many contexts including health (Laric et al., 2009). It is thus hypothesized:

**H1.** Females express higher levels of HI-PC.

Age has been shown to have a positive influence on concern in several contexts including health, with older individuals expressing higher concerns (Laric et al., 2009). Thus, it is hypothesized:

**H2.** Age positively influences HIPC.

The influence of health condition is the subject of debate. Some argue that individuals with health conditions will express lower privacy concerns due to the benefits health technologies can bring (Angst & Agarwal, 2009). In contrast, some argue that individuals with health conditions will express higher privacy concerns due to the sensitivity of their health information. Individuals with sensitive illnesses such as mental health conditions have been found to express high health information privacy concerns (Flynn et al., 2003). Existing literature also shows that individuals who describe their health status as 'poor' health status perceive health information to be more sensitive than those who describe their health as 'good' (Bansal et al., 2010). It is argued that if an individual views their health status as 'poor', they will be concerned about possible misuse or unauthorized access. It is hypothesized:

**H3a.** Poor health status positively influences HIPC.

In addition, healthcare need has been shown to positively influence individuals' intentions to adopt health technologies (Klein, 2007). Individuals with higher healthcare needs have more detailed and potentially, sensitive health records. It is thus posited that these individuals will express higher privacy concerns.

**H3b.** Healthcare need positively influences HIPC.

**Individual Perceptions**

The second set of hypotheses relate to individuals' perceptions. Firstly, perception of health information sensitivity has been found to positively influence individuals' health information privacy concerns (Bansal et al., 2010). If an individual expresses higher perceptions of sensitivity regarding health information, it is likely he/she will be concerned over its use, storage, and privacy. The following hypothesis is presented:

**H4.** Perceived information sensitivity positively influences HIPC.

Secondly, trust perceptions have been shown to reduce information privacy concerns in various contexts including health. Dinev et al. (2016) found that trust in EHR vendors reduced citizens' health information privacy concerns. This study focuses on trust in health technology vendors and hypothesizes that:

**H5a.** Trust perceptions regarding technology vendors negatively influences HIPC.

In addition, it has been argued that individuals’ trust in health professionals will reduce their privacy concerns (Rahim et al., 2013). Thus it is hypothesized:

**H5b.** Trust perceptions regarding health professionals negatively influences HIPC.

Risk perceptions associated with online website vendors have been found to positively influence information privacy concerns (Hong & Thong, 2013). A similar relationship is posited in the context of health technology vendors and health professionals, with high risk perceptions resulting in high HIPC.

**H6a.** Risk perceptions associated with health technology vendors positively influence HIPC.

**H6b.** Risk perceptions associated with health professionals positively influence HIPC.
**Individual Experiences**

Previous studies have shown that awareness of privacy media coverage increases concern regarding one’s personal information (Smith et al., 1996; Malhotra et al., 2004). While this has not been examined in the health context, its relevance is argued due to the large volume of media coverage surrounding privacy and health technologies. A Google search for ‘health technology privacy’ yields approximately 149 million news stories. It is argued that greater awareness of privacy media coverage regarding health and personal information in general will increase individuals’ HIPC. The following hypothesis is presented:

**H7.** Awareness of privacy media coverage is positively related to HIPC.

Lastly, previous experience of privacy invasion has been found to increase concerns in many contexts including health (Bansal et al., 2010). It is thus expected, if individuals believe the privacy of their health data has been previously invaded, they will express higher HIPC. The following hypothesis is presented:

**H8.** Previous privacy invasion positively influences HIPC.

**Proposed Model**

The proposed model below draws on existing literature and theory to examine the antecedents to HIPC.

![Proposed Model Diagram](image)

**Methodology**

This paper forms part of a mixed methods PhD study which explores citizens’ HIPC in-depth. The proposed model was tested using a survey in two countries; the Republic of Ireland, and the United States. These studies were chosen for two reasons. Firstly, the health systems in both countries vary greatly. Healthcare in Ireland is largely public compared to predominately private in the United States. Ireland lags behind other countries in terms of health ICT implementation, but health ICTs are extremely prevalent in the U.S., thus, U.S. citizens have far greater exposure to ICTs in the health setting. In terms of citizens’ mHealth usage, 19% of U.S. adults with a smartphone used an mHealth application in 2012 (Fox and Duggan, 2012), but there are no statistics indicative of usage by Irish adults. Secondly, as the majority of information privacy studies utilise U.S. samples, this study answers the call for studies which utilise
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European samples (Bélanger & Crossler, 2011). Furthermore, as this study extends antecedents and the IPC measure to the health context, these relationships are compared across both countries. Ethical approval was received prior to data collection. The survey was pilot tested among academic experts and a convenience sample of citizens to ensure comprehensibility. In both countries, an email invitation was sent to several groups including University students (Undergraduate and Postgraduate), staff, alumni, members of community health and IT based initiatives, and individuals working in various industries. The aim of the sampling strategy was to capture citizens from different backgrounds in both countries. A total of 447 complete responses were received, (202= U.S., 245= Ireland). In terms of gender, 61% of respondents were female and 39% were male. With regards to age, 25% were aged between 18 and 24, 47% were aged 25-49, and the remaining 28% were 50 and over. Many respondents had used the internet for over 15 years (43%), 29% had 10-15 years’ experience, 21% had between 5-10 years of experience.

Measurement of Variables

This section provides an outline of the measures used. Poor health status and healthcare need were measured using three items from Bansal et al. (2010) and Angst & Agarwal (2009) respectively. Perceived sensitivity was measured using 12 items based on Laric et al. (2009). Trust perceptions regarding health technology vendors and health professionals were measured using six items from Hong and Thong (2013), and Li et al. (2014). Risk perceptions associated with health technology vendors and health professionals were measured using four items based on Hong and Thong (2013), and Li et al. (2014). Awareness of media coverage was measured using two items based on Smith et al. (1996). Previous privacy invasion experience was measured using one item from Bansal et al. (2010). One item scales are acceptable when the concept is clearly understood (Hair et al., 2010). Lastly, HIPC was measured by adapting Hong and Thong’s (2013) IPC measure to the health context. The new HIP measure consists of six first order factors, which load onto a second order general factor. Experience with relevant technologies has been found to have mixed impacts on information privacy concerns. Thus, technology experience was not included as an antecedent. However, prior experience using the internet as a source of health information (Kim & Park, 2012), and prior experience using health technologies were included as control variables. Education, and employment status were also control variables.

Data Analysis

The data met the thresholds necessary to conduct multivariate analysis in terms of skewness, linearity, and kurtosis (Hair et al., 2012). Confirmatory factor analysis (CFA) was conducted in AMOS21 to test the proposed structure of the measurement model. Due to low loadings, some items were dropped including SENS1, and SENS3 from perceived sensitivity, TRUH5 and TRUH2 from trust in health professionals, and TRUT5 from trust in technology vendors. The measurement model indicated good fit, exceeding all thresholds recommended by Hair et al. (2010) for a sample size of >250 (min/df: 1.930, CFI: .933, RMSEA: .046, SRMR: .0516). The next stage of analysis involved validity and reliability testing. Firstly, to test for convergent validity, the AVE (average variance extracted) was calculated. The AVE for each construct was above the recommended .50, indicating convergent validity (Hair et al, 2010). Secondly, discriminant validity of all constructs was tested by comparing the square root of the AVE with inter-factor correlations. The square root of the AVE was greater than the correlations, indicating discriminant validity for all factors. Lastly, the reliability of constructs was tested by calculating the composite reliability (CR). All constructs were reliable with CR scores exceeding .70 (Health status .82, Healthcare need .78, Sensitivity .96, Trust in technology vendors .87, Trust in health professionals .81, Risk associated with technology vendors .92, Risk associated with health professionals .92, Media Coverage awareness .77). The testing of endogenous and exogenous variables simultaneously can foster concerns regarding common method bias (CMB). During questionnaire design, several procedures were followed to limit the potential effects of CMB including promising confidentiality and ensuring all items were unambiguous (Podsakoff et al., 2003). To statistically test for CMB, the common latent factor approach (CLF) was followed (Podsakoff et al., 2003). A CLF was added to the CFA, and the standardized regression weights were compared before and after adding the CLF. The majority of items did not experience a change but three items experienced change in delta between .200 and .300. To account for the effects of CMB, the CLF was retained and common method bias adjusted composites were imputed for subsequent analysis (Gaskin, 2012). Due to inclusion of two nationalities, and the plan to compare the relationships across these groups, invariance tests were performed. Firstly, to test for configural
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invariance, the data was spilt based on nationality. Upon splitting the data, the measurement model fit remained adequate (cmin/df: 1.642, CFI: .904, RMSEA: .038, SRMR: .0607). The two groups were then constrained to be equal. The model still indicated adequate fit. All reliability and validity thresholds were also met thus indicating that the groups are configurally invariant. Partial metric invariance was also achieved, as at least one item on each factor was metrically invariant across both groups (MacKenzie et al., 2011). The next stage of the analysis involved testing the structural model using structural equation modeling. The data was again spilt. The model retained good fit (cmin/df: 1.783, CFI: .941, RMSEA: .042, SRMR: .0587). Each hypothesis was compared across both groups to identify any significant differences in relationships. Table 3 outlines the results for each hypothesis.

<table>
<thead>
<tr>
<th>Hypothesis</th>
<th>Ireland</th>
<th>U.S.</th>
<th>Difference</th>
</tr>
</thead>
<tbody>
<tr>
<td>H1. Females express higher levels of HIPC</td>
<td>(-.111) *</td>
<td>(-.079)n.s</td>
<td>(-.0.069) n.s</td>
</tr>
<tr>
<td>H2. Age positively influences HIPC</td>
<td>(.256) ***</td>
<td>(.139) *</td>
<td>(.0.679) n.s</td>
</tr>
<tr>
<td>H3a. Poor health status positively influences HIPC</td>
<td>(.044) n.s</td>
<td>(.021) n.s</td>
<td>(-.0.593) n.s</td>
</tr>
<tr>
<td>H3b. Healthcare need positively impacts HIPC.</td>
<td>(.214) **</td>
<td>(.043) n.s</td>
<td>(.1.620) n.s</td>
</tr>
<tr>
<td>H4. Perceived sensitivity positively influences HIPC.</td>
<td>(.276) ***</td>
<td>(.135) *</td>
<td>(1.090) n.s</td>
</tr>
<tr>
<td>H5a. Trust perceptions regarding health technology vendors negatively influences HIPC.</td>
<td>(.217) **</td>
<td>(.066) n.s</td>
<td>(-2.565) *</td>
</tr>
<tr>
<td>H5b. Trust perceptions regarding health professionals negatively influences HIPC.</td>
<td>(.238) ***</td>
<td>(.011) n.s</td>
<td>(2.038) *</td>
</tr>
<tr>
<td>H6a. Risk perceptions regarding health technology vendors negatively influences HIPC.</td>
<td>(.090) n.s</td>
<td>(.254) **</td>
<td>(-1.653) †</td>
</tr>
<tr>
<td>H6b. Risk perceptions regarding health professionals negatively influences HIPC.</td>
<td>(.385) ***</td>
<td>(.278) ***</td>
<td>(0.567) n.s</td>
</tr>
<tr>
<td>H7. Privacy media coverage is positively related to HIPC.</td>
<td>(.047) n.s</td>
<td>(.126) *</td>
<td>(-1.033) n.s</td>
</tr>
<tr>
<td>H8. Past Privacy Invasion positively influences HIPC.</td>
<td>(.039) n.s</td>
<td>(.014) n.s</td>
<td>(0.245) n.s</td>
</tr>
</tbody>
</table>

Note: n.s not significant, † p-value < 0.10, * p-value < 0.05, ** p-value < 0.01, *** p-value < 0.001

Table 3. Hypotheses Testing

Findings

Firstly, it was hypothesized that females would express higher HIPC than males. However, males expressed significantly higher HIPC among the Irish sample. This relationship was insignificant for the U.S. sample. Thus H1 is not supported. Secondly, H2 posited that age would positively influence HIPC. This relationship was evident in both samples, supporting H2. Thirdly, H3a proposed a positive relationship between health status and HIPC. This relationship was insignificant in both samples, rejecting H3a. The next hypothesis posited that greater healthcare need would be associated with higher HIPC. This relationship was supported among the Irish sample (p<.01), but not in the U.S. sample. Thus H3b is partially supported. H4 posited that perceived sensitivity would positively influence HIPC. This relationship was significant in both countries supporting H4 (Irish = p<.001, U.S. = p<.05). Next, it was hypothesized (H5a) that trust in health technology vendors would reduce HIPC. This relationship was supported among the Irish sample (p<.01), but not in the U.S. sample. This relationship was also significantly different across the two groups (p<.05). H5b posited that trust in health professionals would negatively influence HIPC. In contrast, trust in health professionals had a positive relationship with HIPC in the Irish sample. The relationship was insignificant among the U.S. sample. The relationship was a significant difference in the relationship between the two nationalities. The following two hypotheses related to risk. It was posited that risk beliefs regarding health technology vendors would increase HIPC. This relationship was positive and significant (p<.01) among the U.S. sample but insignificant among the Irish sample. Therefore, H6a is partially supported. The hypothesized positive relationship between risk beliefs associated with health professionals and HIPC was significant in both samples (p<.01). H6b is therefore supported. It was hypothesized that awareness of privacy media coverage would positively influence HIPC. This relationship was supported (p<.05) among the U.S. sample but not the Irish sample. Therefore, H7 is partially supported. Lastly, it was posited that privacy invasion experience would positively influence HIPC. This relationship was insignificant across both samples, rejecting H8.
Discussion

This study examined the predictors of HIPC. The model was tested in two countries, explaining 24.6% of variance in HIPC for the U.S. sample, and 37.8% for the Irish sample. This section discusses the findings in terms of hypotheses, contributions, limitations, and directions for future research.

**Individual Characteristics**

The study found that males expressed higher HIPC than females. This contradicts previous findings such as Laric et al. (2009) who found that females expressed higher privacy concerns regarding several health data types. While Laric et al. (2009) asked respondents if they were concerned for the privacy of each health data type, this study measured concern HIPC across six dimensions. The study shows than men, particularly in Ireland express higher concerns regarding the privacy of their health data across these six dimensions. Interviews in the next stage of this study explore the reasons underlying the differences in concern between males and females. Secondly, older individuals expressed higher HIPC. This extends previous findings from Laric et al. (2009), who found that older individuals expressed higher concerns regarding several health data types. It is argued that older citizens can benefit most from health ICTs as they require more health services (Li et al., 2014). In addition, older citizens’ personal adoption of mHealth can reduce the financial burden on health services (PWC, 2013). However, this group are viewed as less likely to adopt due to privacy and trust issues (Or et al., 2011). For health organizations introducing health technologies such as EHRs, it is important to ensure the information privacy concerns of all groups including older citizens are addressed prior to implementation. This could potentially be achieved by ensuring individuals are informed about these technologies and educated on how they influence their privacy. To increase mHealth adoption among older citizens, mHealth technology vendors should address their health information privacy concerns. A fruitful avenue for future research would be to test the efficacy of different efforts to reduce HIPC across different age groups, such as educational messages (Angst and Agarwal, 2009), or offering citizens control over their data in these technologies. Health status did not significantly influence HIPC. Higher healthcare needs increased HIPC among the Irish sample only. Previous studies also provide contrasting results, individuals with chronic conditions willingly disclose health data (Lafky & Horan, 2011), but individuals with sensitive conditions express high HIPC (Flynn et al., 2003). Perhaps, one’s perception of how sensitive their condition is, influences HIPC more than their perception of their overall health. The role of health variables requires further exploration, to identify subtle differences across health conditions, nationalities, or age groups.

**Individual Perceptions**

Perceived sensitivity positively influenced HIPC reinforcing previous findings (Bansal et al., 2010). This also supports the information boundary theory, showing that the more sensitive individuals perceive health data to be, the greater their concerns are regarding the privacy of this data. The influence of trust in health technology vendors on HIPC was negative among the Irish sample. This suggests if individuals trust health technology vendors, they will express lower HIPC. Future research could explore health technology vendors’ efforts to build trust as a means of reducing HIPC and increasing adoption. Both trust in health technology vendors and health professionals were insignificant among the U.S. sample. For the Irish sample, trust in health professionals increased HIPC. There are a number of possible explanations. Firstly, trust was measured in terms of health professionals’ integrity and benevolence with individuals’ health data. Thus individuals may trust the intentions of health professionals, but may not trust their ability to protect their health data. The influence of trust on HIPC is explored further at a later stage of this study through interviews with Irish and U.S. citizens. Risk beliefs associated with health technology vendors only increased HIPC in the U.S. Individuals may perceive the risks are high, but they may not use health technologies and thus believe they are not at risk. Risk beliefs associated with health professionals positively influenced HIPC. If individuals believe disclosing health data is risky, they express higher HIPC. Technology vendors should explore methods to reduce risk perceptions, perhaps through fostering trust.

**Individual Experiences**

Privacy related media coverage positively influenced HIPC in the U.S. data, but not in the Irish sample. Individuals may be aware of privacy news stories but may not believe they are personally at risk to such
outcomes. Lastly, it was proposed that individuals who had previous privacy invasion experience would express high HIPC. This relationship was insignificant in both samples. In terms of the protection motivation theory, the study shows that individuals do appraise threats by considering media coverage, and risks associated with disclosure either to health professionals or health technology vendors. Trust can partially negate these threats. The interviews in the next stage of this study further explore the factors influencing individuals' threat and coping appraisals, to determine their influence on individuals' HIPC.

Conclusion

Our understanding of information privacy remains fragmented particularly in the under examined health context. To date, a small number of studies have explored one or two antecedents HIPC. In order to address and appease individuals’ HIPC, it is imperative to identify and understand how different factors influence individuals’ HIPC. This paper integrates information privacy theories and synthesizes empirical findings to develop a framework for testing the predictors of HIPC. The paper also adapts and tests a more comprehensive measure of HIPC. The framework is tested in two countries. The findings illustrate that individual characteristics such as age, and individual perceptions regarding sensitivity, trust and risk, can all influence HIPC, but these findings vary among U.S. and Irish citizens. This paper provides a strong initial insight into the drivers of HIPC. These insights are developed further in the next stage of this study.

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