

# Can Offering Patients' Access to PHR Improve the Sustainability of HIEs?

*Full Paper*

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## Abstract

Health Information Exchange (HIE) are multi-sided platforms that facilitate the sharing of patient health information between providers, payers, etc. across organizations within a region, community or hospital system. HIE benefits to payers and providers include lower cost, faster services, and better health outcome. These benefits are not achieved unless patients consent to share their records. In this research we investigate if HIEs can increase consent rates by offering PHR services to patients and making them active participants in the HIE system. The paper makes a theoretical contribution to research by extending the UTAT model with two types of trust that are critical for patient consent. The findings impact practice. Utilizing 395 participants in a randomized experimental survey design and multi-group invariance structural equation modeling (SEM) we find that PHR will help sustain HIE. In addition, PHR empowers trust in the system and the users.

## Keywords

HIE, PHR, Trust, UTAUT, Information Sharing.

## Introduction

Health Information Exchanges (HIEs) are multisided platforms that facilitate the sharing of patient health information between many participating sides: patients, various types of providers such as hospitals, primary care physicians, lab test providers, other providers, etc. (Kuperman 2011). Typically, providers port patient medical records to exchanges or their edge servers for other physicians to access when needed. The idea being that the entire patient history is available to any physician treating the patient. Patients often see a variety of physicians for the different ailments and the idea of sharing allows physicians to understand the patient medical history prior to delivery of care. The benefits stemming from such a practice is the avoidance of duplicate tests when possible and the availability of the record itself. This potentially could lead to greater practice efficiency and lower costs for payers (Insurance companies) who now do not have to pay for duplication. Providers also benefit by having the entire patient information available to them for making decisions about patients. While the financial benefits to provider practices is not well established, federal incentives and penalties stemming from Meaningful Use Initiatives provided the motivation for greater participation. Availability of patient records to providers also ensures that patients do not receive prescriptions that interact with other prescription drugs they are taking. This leads to better patient safety. As structured, the parties that benefit the most are the payers (Insurance companies) and then to an extent physicians in terms of cost and practice efficiencies. Patients do benefit not necessarily by lower cost as often such savings are often not passed on to patients but by the availability of their medical history to the attending provider. It benefits payers and indirectly providers on occasion. Ambulatory Care practices have not readily adopted HIE access for a variety of reasons. Often ambulatory practices only upload Continuity of Care Record (CCR) document to exchanges. Health Information Exchanges cannot share patients' PHI with physicians who are part of the health exchange without getting consent from the patients (Tripathi et al. 2009). The survival of exchanges is therefore linked to physician adoption. Physician adoption is better if a greater number of patients consent to sharing information, however consent rate is still not up to the expectations according to (Furukawa et al. 2014). Further, most patients are passive participants of exchanges even when they opt to share as they are only informed of their benefits that stems from consenting to share their PHI. However, if patients become active participants in Health Information Exchanges, that ownership and

participation relationship could change the dynamics in terms of sustainability of HIE. Further, it also opens up avenues for revenue generation and a wide variety of specialized services that HIEs can offer in the future. This is especially true as HIEs of the future will likely contain the medical records of other family members and these can be harnessed for better preventive care among other things. A mechanism to engage patients, is for of HIEs to offer Patient Health Record facilities to patients. A personal health record (PHR) is an electronic application used by patients to maintain and manage their health information in a private, secure, and confidential environment. There is a marginal cost to providing this facility. However, offering PHR services also allows patients to control what information they would like to share and with whom they would like that information to be shared.

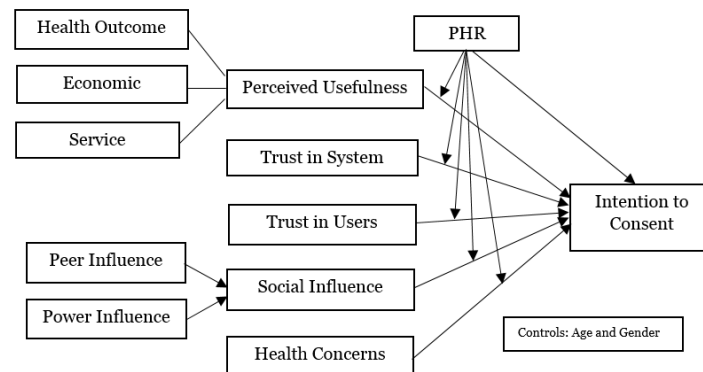
In this study, we investigate how to promote HIEs through incorporating personal health record (PHR) as an additional service to garner more patients consent with full knowledge of the benefits and dis-benefits of sharing PHI, especially when the choices provided are to share everything with all other providers or not to share PHI at all. PHR allows patients to access their information at anytime. Currently PHR is a stand-alone application that is not part of HIEs. The benefits of PHR include empowering patients with information about their health and thus help patients' better maintain their health and prevent risks (Agarwal et al. 2013). Unlike standalone PHR systems, incorporating PHR with HIE obviates the need to port data into the system as that data already exists in the HIE and is kept updated by providers. This paper attempts to answer two main research questions: Can PHR be used to promote higher HIE consent? How does PHR, as an additional service, change the relationship between independent variables such as trust in the system and trust in user) and intention to consent? Using a randomized experimental survey design we try to answer these questions. We contribute to theory by extending the UTAUT model in the context of sharing health information electronically. We conceptualize and empirically develop a second order perceived usefulness factor in the context of sharing health information electronically. We also provide practical insights on how to sustain HIEs and increase consent rate by offering PHR as an additional service to promote HIEs.

## **Related Work**

Most of the current research is focused on investigating the barriers of adoptions for healthcare providers, and finding ways to ease the process and enhance the experiences. Although, the patient is presumed the central beneficial of the technology, limited literature has investigated the patients' side of the equation. In this section, we highlight some of the literature in the information sharing in health information systems. In general, there is a positive attitude towards HIEs, however the attitude does not translate into sharing intention or behavior. Yaraghi et al. (2015) suggest that older and female patients have a higher tendency to sharing their PHI via HIEs. Caine and Hanania (2012) findings suggest that patients do not want all of their medical information shared with all possible recipients. Although type of information that can be shared and type of recipient that can access the information varied by patients, all patients agreed to partial access. On the contrary, Adams et al. (2004) report that majority of respondents would not restrict access to their shared information, and Hassol et al. (2004) found that most patients had positive attitude toward the user of their information in EHR and were mostly not concerned with the privacy of their information. Likewise, Ancker et al. (2012) indicate positive consumers' attitude towards the use of HIE and suggests addressing security concerns. Simon et al. (2009) investigated the barriers to consent using 62 patients in a focus group. The study reports three main concerns: security concerns, lack of knowledge of possible benefit to an individual's health, and the need for more information about the consent process. Grande et al. (2013) find that the sensitivity of the information is not barrier for sharing. Patients focus more on how the information will be used rather than what information is used.

Yasnoff et al. (2013) emphasize that there is a need to investigate ways to overcome barriers to health information sharing and increase sharing. Demirezen et al. (2016) suggest that HIEs have to offer value-added services to attract more healthcare providers and sustain the systems. Yaraghi et al. (2014) explores drivers of HIE adoption by healthcare providers and find that have large market share and high number of shared patients are more likely to adopt than others. Despite the vast extant of studies relating to HIEs and concerns about security and privacy, prior research has not addressed the issue of HIEs providing PHR system to patients. This research is important as PHRs offered to patients by HIEs could improve patient involvement and engagement with HIEs, thereby improving the sustainability.

## Conceptual Model Development



**Figure 1 – Conceptual Model**

This work adapts the Unified Theory of Acceptance and Use of Technology Model (UTAUT) (Venkatesh et al. 2003) to the context of health information exchanges. This study investigates how trust in the system and users, perceived usefulness, health concerns, and social influence affect the intention to consent. It also explores how offering patients PHR services impacts this relationships as shown in Figure 1. We integrate trust variables into the UTAUT model because trust is main factor in systems that focus on the collection and use of personal information (Gefen et al. 2003). We capture performance expectancy in the UTAUT model through a second order perceived usefulness variable. We use health concern as a facilitating condition in the healthcare context. In addition, we improve social influence factor by separating it into two factors representing peer pressure (such as family and friends) and power influence (such as physicians). We also investigate how using PHR as an additional service that comes with HIE could improve the consent rate.

### PHR

The PHR is a tool that patients can use to collect, track and share past and current information about their health. A PHR is information about patients' health compiled and maintained by patients. This allows patients persistent access to your complete health information. In a PHR, patients may share their health records with people they choose. Revoking access at any time is also under the patients' control. Demirezen et al. (2016) suggest that HIEs have to offer value-added services to sustain the systems. We argue that offering PHR to patients as a result of their consent to HIEs will attract more patients and increase the consent rate. PHR will add value to the HIE system as patients will gain knowledge about their health and get motivated to maintain healthy lives. Patients will perceive greater value from participating in HIEs and therefore more likely to consent. We therefore hypothesize that:

**H1:** Offering PHR with HIEs will be positively associated with intention to consent

### Trust in System

Trust in the system reflects on the system's ability to handle patients information safely and reliably (Dinev and Hart 2006). The more trust people have in the system the more they will be engaged in the system (Abdelhamid et al. 2015). Trust has been associated with increased usability; people will use the system more if they trust it. Gefen et al. (2003) emphasize that the impact of trust in the system on the intention to use becomes even more important when engagement include probability of risky behavior. Using online survey of student population, Bansal et al. (2010) suggest that peoples' trust in health websites is positively associated with intention to disclose personal health information online. Trust can be associated to the system itself and its ability to protect information from people who can illegally breach the system and misuse the information. The probability of any of these type or misuse happening increases when information is exposed and shared across multiple systems. Therefore, increased trust is expected to yield more patients consenting to share their personal health information.

**H2a:** Trust in the system is positively associated with the intent to consent

**H2b:** Offering PHR with HIEs changes the association between trust in system and intention to consent

### **Trust in Users**

The extent to which a patient has trust in physician and users of system who have access to the patients' information. Consent to sharing personal health information implies that patients give users the right to view personal information such lab tests, medication prescriptions, medical conditions, doctors' notes, and personal characteristics (such as name and age). This includes sharing share irrelevant sensitive medical history with primary care physicians providing care for an entirely different. Trust in users is a major factor in health information context (Venkatesan et al. 2016) and thus should be included in the UTAUT in healthcare context. (Li et al. 2012) argue that patients trust in clinicians is positively associated with attitude towards sharing personal health. Dhopeswarkar et al. (2012) state that patients trust physicians when it comes to having access to health information. However, most people want to know who viewed their information. For patients with HIV, trust in clinicians is associated with positive attitude toward sharing health information (Teixeira et al. 2011).

**H3a:** Trust in users is positively associated with the intent to consent

**H3b:** Offering PHR with HIEs changes the association between trust in users and intention to consent

### **Social Influence**

Social influence is one of the main factors in the UTAUT model (Venkatesh et al. 2003). Social influence has been recognized as an influencing factor on people's behavioral intention (Venkatesh and Davis 2000). Levine and Moreland (2008) emphasize that when people have to make individual decisions, they are highly influenced the judgments of other people who are close to them. Social influence is a reason why people may or may not donate (Fiske and Taylor 2013). In the healthcare context, Kim and Park (2012) suggest that social influence play an important role in promoting the use of health information technology among patients.

**H4a:** Social influence is positively associated with the intention to consent

**H4b:** Offering PHR with HIEs changes the association between social influence and intention to consent

### **Health Concern**

Health concern refers to the degree to which health concerns are part of an individual's daily lifestyle. Bulgurcu et al. (2010) suggest that people's beliefs about the consequences of a behavior have a direct influence in their intention to engage. The commonly held belief is that when the entire medical history of a person is available at hand, the delivery of health can be better tailored at an individual level resulting in better quality and timely care (Yaraghi 2015a). When patients consent to sharing their PHI with providers, they are expecting physicians to use this information make better decisions (Patel et al. 2011). Thus, patients are sharing information because they are concern about their health and want to seek better health outcome through giving doctors the information they need to give better opinions. Therefore, the higher the health concern the higher the individual's willingness to consent

**H5a:** Health concern is positively associated with the intention to consent

**H5b:** Offering PHR with HIEs changes the association between health concern and intention to consent

### **Perceived Usefulness**

UTUAT defined performance expectancy as the degree to which the system can help them achieve better goals (Venkatesh et al. 2003). In healthcare context, patients goals relate to outcomes and services related to their personal health. Thus, we defined perceived usefulness in the health information exchange context as the degree to which patients believe that the system will help them achieve better health outcomes, economic outcomes, and services. We conceptualize usefulness to include health outcome, better and faster service, and economic gains. Yaraghi (2015b) suggest that HIEs reduce costs, Carr et al. (2014) argue that HIEs improve health outcomes, and Williams et al. (2012) emphasize that HIEs improves the quality of service provided to patients. Platt and Kardia (2015) suggest that perceived

benefits and quality of care are positively associated with engagement in the system. Ancker et al. (2012) use data from The Empire State Poll of adult New York State and find that majority of respondents believe HIE improves the quality of care. Fontaine et al. (2010) found that improving the quality of care are motivators for adoption of HIE.

**H6a:** Perceived usefulness (PU) is positively associated with the intention to consent

**H6b:** Offering PHR with HIEs changes the association between PU and intention to consent

## Methodology

### Procedure

We conducted an experimental survey design using 395 participants through Amazon MTurk. Incentive is provided to participants through Amazon. MTurk is as reliable as traditional pools (Ayyagari et al. 2011). Online survey has been used in top Information Systems journals in the context of sharing health information electronically (Angst and Agarwal 2009). Participants were randomly assigned to one of two groups [(A) HIE or (B) HIE + PHR]. Participants in group A were asked about their intention to consent to an HIE system. Participants in group B were asked about their intention to consent to an HIE that offers PHR as a value added for patients to access and manage their information. MTurk is reliable, valid and effective data collection approach (Steelman et al. 2014).

### Measures

All constructs were operationalized using existing scales from previous studies. In the present study, the items from the original scale were slightly modified to be suitable in healthcare context. The survey questionnaire consisted of items measuring constructs in the conceptual model, respondents scored each of these questions on a seven-point Likert-type scale (1 = strongly disagree to 7 = strongly agree). The items for intention to consent and trust in the system and in users were adapted from Malhotra et al. (2004). The items for social influence were adapted from Wu (2009). The items for perceived usefulness Davis (1989). Items for health concerns were adapted from adapted (Jayanti and Burns 1998). PHR is dummy variable (1= group B – HIE+PHR, 0=HIE only). Gender and age were used as control variables.

### Second-order Perceived Usefulness

We construct a second order reflective construct of Perceived Usefulness. We validate the second order factor statistically following a set of guidelines using confirmatory factor analysis (CFA) (Hong and Thong 2013; Rindskopf and Rose 1988). Marsh and Hocevar (1985) suggest that when the lower order factors have high correlation among each other or suffer from multicollinearity then a higher may exist. If there is a multicollinearity then the coefficient of the model will be biased (Reddy and LaBarbera 1985). The Variance Inflation Factor (VIF) for all three factors are well below the cutoff of 10 (Tabachnick and Fidell 2013) with the highest being 2.89. However, correlation among the variables are relatively high with numbers between 0.73 and 0.74. Table 1 shows correlation among the three factors and their VIFs.

	<b>1</b>	<b>2</b>	<b>3</b>
<b>Perceived Health Outcome Usefulness</b>	<b>2.48</b>		
<b>Perceived Economic Usefulness</b>	0.70	<b>2.52</b>	
<b>Perceived Service Usefulness</b>	0.74	0.75	<b>2.89</b>
<b>Bold numbers in diagonal are VIFs</b>			

**Table 1. Lower Order Factors Correlation**

The correlation among the three factors suggest a possible higher order factor. To empirically test the higher order factor against other lower level possible factors, we run all possible measurement models and compare their goodness of fit indices as indicated by (Rindskopf and Rose 1988). Rindskopf and Rose (1988) indicate a requirement of at least three first-order factor for a one second order factor. They identify a set of models to compare: (a) a one-factor model in which all items load on one general factor, which is labeled as model 1 (b) a group-factor model in which there are several factors (that are

correlated) that are associated with three or four items each, the model is labeled model 2 (c) a second-order factor model in which there is one second order factor that consist of several first-order factors each assigned to three or more items. Each of the items in all models have a residual variable.

Following criteria by Rindskopf and Rose (1988) we compare the model fit statistics in Table 2. We examined AIC and CAIC indices as suggested by Malhotra et al. (2004), the smaller the AIC and CAIC the better the measurement model. Model 3 show the smallest AIC and CAIC among the three models suggesting a better fit for a second order factor. It is also suggested that the smaller the  $X^2$  the better the model. Model 3 is the model with the smallest  $X^2$ . We then used criteria established by Hu and Bentler (1999) to compare model fit indices of the three measurement models. Hu and Bentler (1999) suggest (a) a comparative fit index (CFI) > 0.90 (b) Root mean square error of approximation (RMSEA) that is < 0.08 (c) Root mean square residual (RMSR) < 0.1 and (d) a Tucker Lewis Index (TLI) > 0.9. Model 1 does not meet most of the criteria for good measurement model.

	<b>Model 1</b>	<b>Model 2</b>	<b>Model 3</b>
<b>Fit Indices</b>	<b>1st-order</b>	<b>1st-order</b>	<b>2nd-order</b>
$\chi^2$	431.378	254.905	172.696
Df	35	32	32
$\chi^2/df$	12.325	7.966	5.397
Goodness-of-fit (GFI)	0.803	0.898	0.921
Adjusted goodness-of-fit (AGFI)	0.690	0.825	0.863
Normalized fit index (NFI)	0.852	0.932	0.941
Comparative fit index (CFI)	0.862	0.940	0.951
Tucker Lewis Index (TLI)	0.822	0.916	0.931
Root mean square residual (RMSR)	0.044	0.056	0.038
Root mean square error of approximation (RMSEA)	0.170	0.133	0.06
AIC	471.378	300.905	218.696
CAIC	570.956	415.419	333.210

**[The darker the shading the better the model]**

**Table 2. Perceived Usefulness Models Comparison**

Comparing Model 2 to Model 3, it can be noted that Model 3 is better than Model 2 in each of the model fit indices. Thus, a second order construct is supported by the empirical analysis. For example, GFI improves from 0.898 in model 2 to 0.921 in model 3, NFI improves from 0.932 to 0.941, CFI improves from 0.940 to 0.951, TLI improves from 0.916 to 0.931, and RMSEA improves by decreasing from a bad fit index of 0.133 in model 2 to a 0.06 in Model 3 indicating a good fit indicating a better model.

The results of the three measurement model suggest that Model 3 is recommended and thus perceived usefulness can be modeled using three first-order one second-order factors. Therefore, we carry out the validity and reliability analysis of the factors and the items using the second-order model. Table 3 shows the validity and reliability scores for the second order model. All items have high loading ranging from 0.67 to 0.933 and significant loadings indicating convergent validity. The AVE score for each of the three latent variables is higher than 0.5 which is the cutoff for indicating establishing convergent validity. Reliability of the second order factor is 0.928 indicating an excellent overall reliability for the model.

<b>Factors</b>	<b>Item</b>	<b>First-order factors</b>			<b>Second-order factor</b>			
		<b>Loadings</b>	<b>AVE</b>	<b>CR</b>	<b>Loadings</b>	<b>Factor</b>	<b>AVE</b>	<b>CR</b>
Perceived Health Outcome Usefulness	Puh_1	0.827	0.705	0.905	0.862	Perceived Usefulness	0.811	0.928
	Puh_2	0.875						
	Puh_3	0.856						

	Puh_4	0.798					
Perceived Economic Usefulness	Pue_1	0.846	0.661	0.853	0.880		
	Pue_2	0.698					
	Pue_3	0.884					
Perceived Service Usefulness	Pus_1	0.750	0.675	0.861	0.957		
	Pus_2	0.846					
	Pus_3	0.864					

**Table 3. Validity and reliability for the Second-order Construct.**

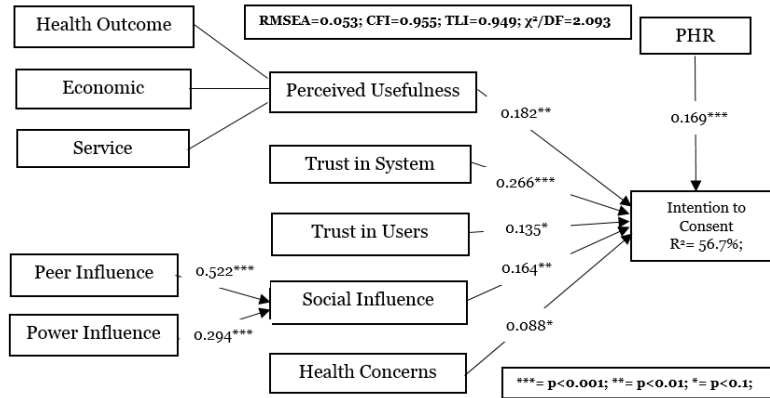
## Measurement Model

We used AMOS to analyze the data. To assess the validity of our measurement model, we performed confirmatory factor analyses (CFA) on all questionnaire items using AMOS. The results reported in CFA loadings for the constructs are very high indicating convergent validity. The goodness of fit indices for our measurement model exceed the threshold showing excellent fit of the measurement model (RMSEA is 0.053, CFI is 0.958, and TL is 0.951). Cronbach Alpha values are all well above the threshold value of point 0.70 (Nunnally and Bernstein 1994). The composite reliability were also all well above the threshold of 0.70 (Joreskog and Sorbom 1989). Convergent validity is assessed by calculating the average variance extracted (AVE) where each indicator is related to only one construct. The AVE values for all constructs exceeded 0.5 which is the desirable cutoff suggesting a convergent validity (Fornell and Larcker 1981). Discriminant validity was established as the AVE values for any two constructs exceeded the squared construct intercorrelation for each pair. Common method variance was assessed through the marker variable technique (Lindell and Whitney 2001).

## Results, Discussion, and Future Work

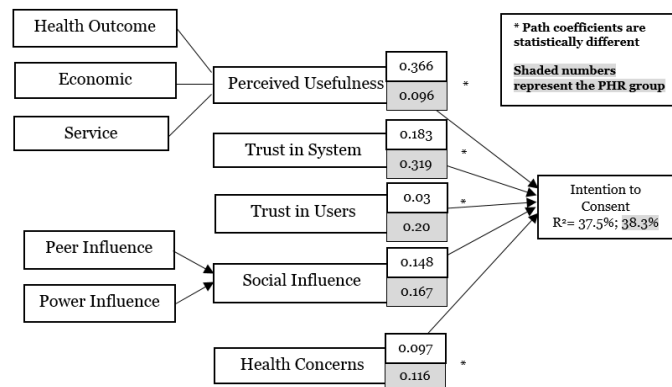
SAS 9.4 was used to recode the data and AMOS 23 was used to run the analysis. Estimates derived from the Structural Equation Modeling (SEM) analysis are used to test the research hypotheses. Figure 2 shows the results for overall impact of PHR as additional service on intention to consent as well as the overall effect of the predictor variables on intention to consent. The model included all 395 participants and overall goodness of fit statistics of the structural model showed indicate a good model fit. The path coefficient of PHR in model 1 is positive and significant ( $\beta = 0.169$ ,  $p < .001$ ) supporting hypothesis 1. Trust in the system has a positive and significant influence on intention to consent ( $\beta = 0.266$ ,  $p < .001$ ) and trust in users also has a positive and significant effect on intention to consent ( $\beta = 0.135$ ,  $p < .1$ ). Thus hypotheses H2a and H2b are both supported. The results in Model 1 also provide support to hypotheses H4a, H5a, and H6a with regards to the influence of social influence ( $\beta = 0.164$ ,  $p < .01$ ), health concern ( $\beta = 0.088$ ,  $p < .1$ ), and perceived usefulness ( $\beta = 0.182$ ,  $p < .01$ ) on the intention to consent. It is also worth noting that peer influence has nearly twice the impact of power influence. Figure 3 shows the difference of the effect of predictor variables on intention to consent between the HIE only group and the HIE+PHR group. The (\*) next to path coefficients indicates a statistical difference between the path coefficients across the two groups. This study explore differences due to adding a PHR service. In order to explore the differences, we divided the survey respondents into two groups: the HIE group and the HIE+PHR group. For HIE group, the model explained 38.5% of the variance in intention to consent. For HIE+PHR group, the model accounted for 38.3% of the variance in intention to consent. Our results show that there some differences in the effects of the determinants on intention to consent. This study conducted a multi-sample tests to investigate the framing differences in the strength of the path coefficients.

To conduct the analysis one path coefficient was constrained to be equal across the two groups. Using a  $\chi^2$  difference test, the resulting model fit was then compared to a base model in which all path coefficients were freely estimated.



**Figure 2. SEM Results for Overall Model**

The overall model is significantly different between the two framing. To test the invariance of all the paths simultaneously, the unconstrained structural model in which all paths parameters were allowed to vary across samples was compared with the constrained model in which all these paths parameters were fixed to be invariant in both groups. The unconstrained structural model resulted in: CFI = 0.907, and RMSEA= 0.077. The estimation of the constrained structural model resulted in: CFI= 0.92, TLI = 0.907, and RMSEA= 0.077. The  $\chi^2$  difference between the two models was significant, leading to rejection of an invariant pattern of causal paths. This indicates that at least one of path coefficients was not the same across the two groups. This result indicate that there is a PHR effect resulting in significant difference between at least one of the predictor variables and the dependent variable. Results shown in Figure 3 provide support for hypotheses H2b, H3b, H5b, and H6b. Hypothesis H4b is not supported. These results indicate that a value added PHR to HIEs significantly changes the relationship between each of the predictor variables and intention to consent. Our findings show that the value PHR empowers trust in system, trust in users, and health concerns as the impact on intention to consent significantly increases. PHR decreases the dependency on users' perception of usefulness. Patients who are more concern about their health will be more likely to consent when they have a system that allows them to manage and maintain their health. Similarly, we find that trust in the and in users lead to higher consent when PHR is added. Thus, PHR improves the role of trust in engaging patients and sustaining HIEs. Our motivation comes from our desire to sustain HIEs by engaging more patients with greater intensity. We propose a way to improve the consent rate in HIEs. Our findings show that a value PHR increases consent rate significantly and thus resulting in sustaining HIEs and engaging patients in their health.



**Figure 3. SEM Results for Multi-group Invariance**

The findings of this result are significant from a practical perspective as it makes patients more vested in HIEs. This allows for revenue generating opportunities to help the sustainability of HIEs. This research also makes several contributions to research. It extends the UTAT model by exploring the impact of two types of trust. Social influence is also viewed in this research as a second order variable. Another theoretical contributions stemming is 'Health concerns' as a driver for patient consent. This has not been studied as part of prior literature and is another contribution to the existing body of literature on HIE and



to UTAT model. These results indicate that a value added PHR to HIEs significantly changes the relationship between each of the predictor variables and intention to consent. Thus the patients' acceptance and use of the technology significantly changes because of the value added by PHR. These results provide theoretical implication on how the UTAUT model is different based on the level of value provided by the technology.

We also provide theoretical contribution to UTAUT by incorporating trust in both the system and users which have been discovered to be key factors when it comes to systems that deal with patients' personal health information. We also provide practical implication that healthcare providers to sustain HIEs by incorporating sub-systems such as PHR that add value to patients and encourage them to consent to HIEs.

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