PLS-SEM path analysis to determine the predictive relevance of e-Health readiness assessment model

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Abstract

Background and significance: There a sizable body of research addressing the evaluation of eHealth/health information technology (HIT) readiness using a standard readiness model in the domain of IS. However, there is a general lack of reliable indicators used in measuring readiness assessment factors, resulting in limited predictability. The availability of reliable measuring tools could help improve outcome of readiness assessments.

Objective: Determining the predictive relevance of developed HIT model

Materials and methods: We collected quantitative data from clinical and non-clinical (administrators) staff at Komfo Anokye Teaching Hospital (KATH), Kumasi Ghana using the traditional in-person distribution of paper-based survey, popularly known as drop and collect survey (DCS). We then used PLS-SEM path analysis to measure the predictive relevance of a block of manifest indicators of the readiness assessment factors.

Results and discussion: Three important readiness assessment factors are thought to define and predict the structure of the KATH HIT/eHealth readiness survey data (Technology readiness (TR); Operational resource readiness (ORR); and Organizational cultural readiness (OCR). As many public healthcare organizations in Ghana have already gone paperless without any reliable HIT/eHealth guiding policy, there is a critical need for reliable HIT/eHealth regulatory policies readiness (RPR) and some improvement in HIT/eHealth strategic planning readiness (core readiness).

Conclusion: The final model (R^2 = 0.558 and Q^2= 0.378) suggest that TR, ORR, and OCR explained 55.8% of the total amount of variance in HIT/eHealth readiness in the case of KATH and the relevance of the overall paths of the model was predictive. Fit values (SRMR = 0.054; d_ULS = 6.717; d_G = 6.231; Chi^2 = 6,795.276; NFI = 0.739). Generally, the GoF for this SEM are encouraging and can substantially be improved.

Word Count: 4,484

Keywords: HIT/eHealth, Readiness assessment model, Measuring tools, Ghana, KATH

INTRODUCTION

Adoption of new information and communication technologies/information system (ICT/IS) in the healthcare environment in developing countries remain low even though much has been written on the potential benefits when properly implemented. Ghana, like many third world countries is still in its nascent stages of achieving meaningful use of information technology (IT) in healthcare (Bedeley and Palvia, 2014). Unlike paper-based folders which are still being used in our hospitals, IS/IT can help provide the reliable and timely information needed for quality and efficient healthcare delivery. In Ghana, the lack of state funding; limited geographical access; and shortage of health workers continue to confront healthcare despite the introduction of the National Health Insurance Scheme (NHIS) and the expansion of Community-Based Health Planning and Services (CHPS) (World Health Organization, 2014). eHealth/health information technology (HIT)[1] is the use of IS/IT in healthcare to help make available accurate health data electronically for exchange among authorised healthcare providers and consumers for the purpose of improving the quality of healthcare delivery irrespective of geographical boundaries.

Many public healthcare organizations in Ghana are going paperless amid many challenges, which include but are not limited to a general lack of ICT infrastructure and experienced health informaticians. Worst yet, is the lack of reliable measuring tools to be used in assessing standard HIT/eHealth readiness assessment factors (e.g. *Core readiness, Engagement and buy-ins readiness, Technological readiness and IT Skills readin*ess) and as such lack of 'normative' HIT/eHealth adoption readiness model (Yusif et al., 2017b). The effect is increased HIT/eHealth implementation failures.

Hospitals and healthcare providers are confronted by the need to enhance care delivery without increasing resource consumption in both developed and developing countries (Maunder et al., 2018). In developing countries, technology readiness is the strongest factor facilitating eHealth adoption and assimilation given the high rate of adoption failure. In developed countries, technology integration is the strongest factor for assimilation in developed countries. This implies that as organisations become more digital, the key determinant of its assimilation shifts from accumulation to integration of technologies. It is unclear how relationships among identified eHealth readiness factors impact on the overall readiness of healthcare institutions to successfully adopt eHealth. As such the objective of this study was to assess the overall

[1] eHealth, HIT and digital health are uses interchangeably in this paper

readiness of KATH to implement eHealth in the context how intra-relationship between unobserved factors strengthens or weakens the relationship with the outcome variable.

The Information Systems (IS) discipline examines socioeconomic systems that are characterized by the interplay between hardware and software on the one hand, as well as individuals, groups, and organizations on the other (Urbach and Ahlemann, 2010, Veinot et al., 2019, Al Sallakh et al., 2017). For example, influence of culture and technology adoption, acceptance, success, and the conditions under which these can be achieved are typical issues that are addressed by IS research (Urbach and Ahlemann, 2010, Scherer et al., 2019, Sunny et al., 2019). In this study, we assess the readiness of Komfo Ankye Teaching Hospital to adopt eHealth as the public hospital is in the process of implementing a HIT/eHealth system using a model developed in earlier study (results presented in another paper). We demonstrate the use of partial least squares –structural equation modeling (PLS-SEM) and argue that this could help to incorporate more assumptions that are realistic and better measurements into HIT/eHealth adoption readiness assessment researches.
The PLS is an alternative to ordinary least square (OLS) regression, canonical correlation, or covariance-based structural equation modeling (SEM) of systems of independent and response variables (Garson, 2016). As a second generation (2G) statistical analysis, the partial least squares (PLS) algorithm has become increasingly popular both in IS research and in other disciplines such as marketing (Albers, 2010). First generation (1G)'s standard regression techniques offer limited modeling capabilities, particularly in terms of causal or complex modeling (Lowry and Gaskin, 2014). Digital health implementation in developing countries are well documented due to lack of rigorous readiness assessment as with lack of models for readiness assessment (Yusif et al., 2017a). Several of the readiness assessment models available have not demonstrated effectiveness, posing difficult research questions that require rigorous research approaches. Research problems are usually difficult to handle by 1G when an outcome is determined not only by direct influences of the predictor variables but also by their unobserved common cause (Kupek, 2006). The failures of IT adoption in the healthcare environment has well been documented with attributed reasons ranging from technical to organisational and human-related but poor evaluation of existing and ongoing similar/related projects remain equally worrisome. This is in part or mostly because unobserved and indirect relationship among independent variables and their impact on the overall outcome variable are not usually accounted for. Thus, a key limitation of standard regression (1G) techniques is their failure to model "latent variables, indirect effects (mediation), multiple group moderation of

multiple effects, and assessing the "goodness" of the proposed (tested) model in comparison with the observed relationships contained in the data" (Lowry and Gaskin, 2014 p.139). On the contrary, as posit Lowry and Gaskin (2014), the key point of structural equation modeling (2G) techniques is their ability for complex causal modeling that dominates recent behavioural research. Therefore, in this study, PLS is employed to simultaneously test the measurement model (relationships between indicators and their corresponding constructs); the structural model (relationships between constructs) (Gil-Garcia, 2008); and to use SEM to determine whether the developed model is valid . The research question sought to answer was:

In what ways do relationships among exogenous (independent) variables impact the relationship between exogenous variable and endogenous (dependent) variable?

THEORY BACKGROUND AND HYPOTHESES

The research model (see Figure 1) is made up of the Technology-Organizational and Environmental factors (TOE) framework (Tornatzky and Fleischer, 1990) and DeLone & McLean Information Systems Success Model (D&M) IS model (Delone and McLean, 2003) in the context of HIT/eHealth adoption readiness in public healthcare organizations in Ghana. TOE has proven to be an effective model for investigating the adoption of technologies by organizations as employed by many studies (Oliveira and Martins, 2011, Dwivedi et al., 2012). For example, Hung et al. (2010) adopted organizational information systems to explore factors that impact the adoption of customer relationship management (CRM) systems. Similarly, Lin (2014), and Teo et al. (2009) as with Pan and Jang (2008) used TOE to investigate firms' adoption of electronic supply chain management systems, adoption of e-Procurement systems and adoption of enterprise resource planning (ERP) systems in the communication environment respectively. Several other studies include but not limited to (Dewi et al., 2018, Hao et al., 2020, Herath et al., 2020, Hue, 2019, Singeh et al., 2020, Arpaci, 2019). Building and implementing eHealth systems is not enough. There needs a comprehensive examination of the various elements of site in terms of system quality[2], information quality[3] and ultimately, service quality[4]. In this study we examine these important factors (Shim and Jo, 2020) using DeLone & McLean Information Systems Success Model (D&M) IS model (Delone and McLean, 2003) by integrating it into the "Technological" component of TOE. Previously,

[2] System quality is the technical make-up (software, data components, user interface and performance of a system that are measured by the ease of use, functionality) of the information system (IS) and its ability of the system to meet use requirement – conformity DELONE, W. & MCLEAN, E. 1992. Information systems success: The quest for the dependent variable. *Information systems research,* 3, 60-95, GORLA, N., SOMERS, T. & WONG, B. 2010. Organizational impact of system quality, information quality, and service quality. *The Journal of Strategic Information Systems,* 19, 207-228, VENKATESH, V. & BALA, H. 2008. Technology acceptance model 3 and a research agenda on interventions. *Decision sciences,* 39, 273-315.

[3] Information quality relates to the quality of output in the context of content, presentation, and relevance of information (Ibid)

[4] Service quality denotes the overall support offered to system users to help in achieving their goals of using the IS (Ibid)

Previous studies that have used DeLone & McLean Information Systems Success Model (D&M) IS model (Delone and Mclean, 2004) include (Dewi et al., 2018, Fanta et al., 2016, Freeze et al., 2019, Kwao et al., 2020, Ojo, 2017, Singeh et al., 2020, Yusif et al., 2020b).

Infrastructure has come to mean those resources and services —whether human, technical, or sociotechnical—that enable, support, and shape activity. Infrastructure is always a social and political matter as much as it is a technical one (Grisot and Vassilakopoulou, 2017, Ribes and Polk, 2014). Technology infrastructure ensures that platforms on which eHealth can be built with input from knowledgeable IT workforce for successful implementation. The implication of this that IT infrastructure is not comprising only physical assets, but also by human resources (Harding et al., 2018). Digital health operational resources from the acquisition of ICT resources such as hardware and software, generally require significant investment upfront plus total cost of ownership. However, there is less evidence on the capital and recurring costs needed to implement and maintain digital health systems and programs (Long et al., 2018, Wang and Ku, 2020). This has particularly been the case when scaling up from small digital health projects to institutionalization. Environmentally, as with funding, regulatory and policy issues are key factors when initiating digital health projects.

Despite the continuing evidence of the positive impact of digital health systems on healthcare accessibility and health outcomes, there still exist no clear-cut policy on how practice of digital health in the context of liability and reimbursement should be administered (Eigner et al., 2019, Mertes and Brüesch, 2018). Different countries, different states and different regions and continents have different policies and regulations regarding details of digital health practice. Digital health and accompanying privacy concerns is discovered by a range of different laws, regulations, and conventions on electronic health records. For example, different approaches towards privacy between advanced countries and their low middle income countries (LMIC) provides platforms for challenges in developing harmonized global privacy standard (William, 2017). Additionally, context of treatment relationship ("the direct bilateral relationship between a patient and the health care professional/health care institution consulted by the patient" (Party, 2007 WP 131, 11) cited in (Fricker et al., 2015) and issues of consent are still grey and need to be explicitly clarified.

In Ghana, most healthcare facilities are implementing and practicing digital health in one form or the other based on their own digital health regulations, which are believed to complement standard regulations of healthcare practice and data protection.

Organizational cultural readiness in the context of top management support, constructive engagement and involvement of all internal stakeholders (all those impacted by the implementation of the system availability of change management tis an important precursor for eHealth adoption (Faber et al., 2017, Yusif et al., 2020a).

Overall, greater investment in national and local healthcare facilities' infrastructure implementation of guidelines for the safe and transparent use and assessment of digital health, incentivization of interoperability, and investment in upskilling of professionals and the public would help support the normalization of digital health would have a positive impact on digital health readiness and implementation (Lennon et al., 2017). As a result, we hypothesised that:

H1: The impact of Operation resource readiness (ORR), and Regulatory policy readiness (RPR) on Technological readiness factors will have positive impact on the readiness of KATH to successfully adopt HIT.

H**2**: The impact of Operational resource readiness (ORR) and Regulatory and policy readiness (RPR) on Organizational cultural readiness (OCR) will have positive impact on the HIT readiness of KATH

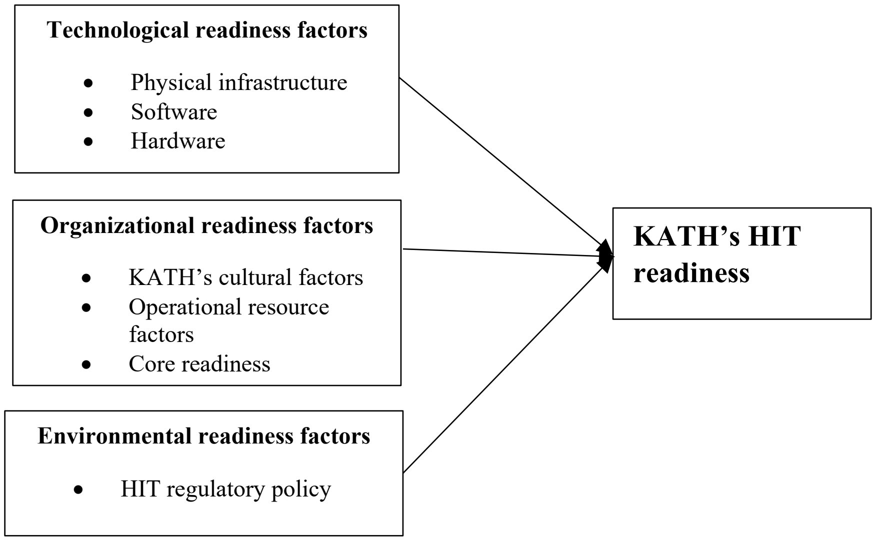
H3: The impact of Regulatory policy readiness (RPR) on *Operational resource readiness* (OPR) will have positive impact on the readiness of KATH to adopt HIT.

H4: Environmental readiness factors such as eHealth *Regulatory and policy* will impact negatively on the readiness of KATH to adopt HIT.

The purpose of strategy formulation is to help organisations to produce effective decisions (doing the right things) shaping the nature and direction of eHealth within societal, legal, economic, and technological bounds (Mettler and Vimarlund, 2011). It helps in the identification of a range of clinical and non-clinical services to be accomplished using HIT (H5) and more importantly further helps in questioning the availability of key leadership capacity in implementing formulated strategies, an attribute of the organizational concept of TOE. However, eHealth strategies adopted healthcare facilities would have taking all factors into consideration to ensure that the strategy is executable or achievable. However, some initially available data suggest that existing HIT strategic documents are too generic/lacks any specifics in the context of having considered all relevant factors. Consequently, it is hypothesized that the impact of the rest of the identified factors on *core readiness* will "spill over" negatively on core readiness:

H5: The impact of OCR, ORR, RPR and TR on *Core readiness* will negatively impact the readiness of KATH to adopt HIT.

Figure 1: Research Model

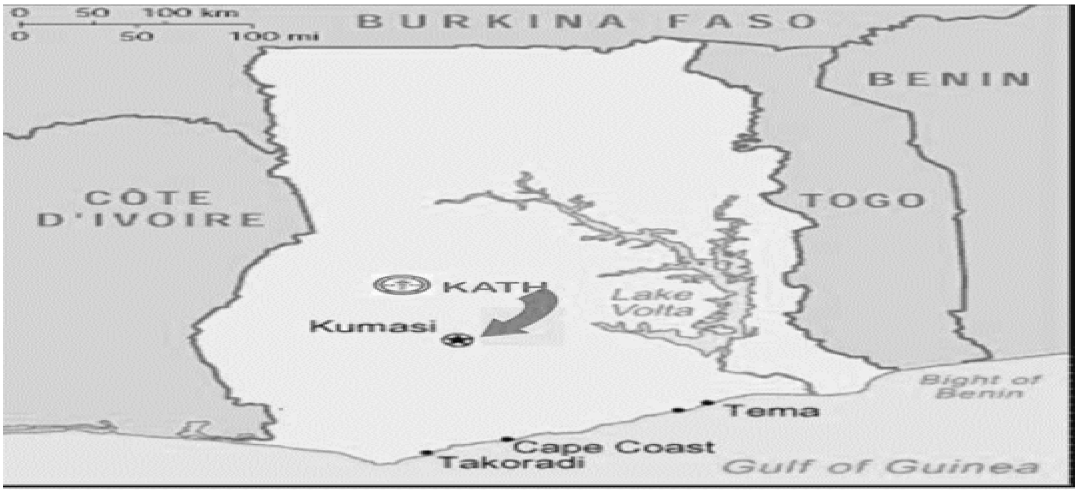


Source: Adapted from Tornatzky and Fleischer (1990)

Ghana and Komfo Anokye Teaching Hospital (KATH)

In our previous standard regression study that validated empirically developed eHealth readiness assessment model with complete reliable indicators (Yusif et al., 2020b), we covered well enough on Ghana and KATH. Figure 2 below illustrates Ghana map and the location of KATH.

Figure 2: Map of Ghana showing the location of KATH in the Ashanti region



Source: Agbokey (2014)

METHODOLOGY

This study uses mixed methodology, specifically exploratory sequential where results of analysed qualitative data build quantitative data collection in a form of case study in which views of clinical[5] and non-clinical officers[6] of KATH on the readiness of their institution to successfully expand on their HAMS systems and/or implement other intending HIT related systems sought. The study began after systematic literature review (see Yusif et al. (2017b)) and qualitative study involving 13 heads of HIT from various public hospitals, leaders of HIT/eHealth related projects in Ghana and senior academics (see Appendix 1 for details of research population matrix).

This case study includes quantitative method with results of initial analysed qualitative data being input in developing survey instrument. The survey was timely as it provided a broad overview of the views of both clinical and non-clinical staff on the implementation of HAMS and hatching of the idea to extend its functionalities and/or implement other HIT systems. Ethical approvals were granted from both USQ (**H13REA149**) and KATH (**CHRPE/AP/119/17**) respectively. The collection of quantitative data from KATH (see Appendix 2 for survey population) in Kumasi, the capital of the Ashanti region of Ghana from March to April 2017 using a survey instrument developed from an initial thematically analysed collected qualitative data. 298 of the total population invited completed and returned their questionnaires.

We used the traditional in-person distribution of paper-based questionnaire, popularly known

[5] Medical doctors, pharmacists, RNs, Lab technicians
[6] Administrative officers

as drop and collect survey (DCS). It is the one data collection technique that appears to avoid most of the shortcomings of the other survey methods including on-line, telephone and postal in developing countries. By combining the strengths and avoiding the weaknesses of face-to-face and postal surveys, DCS provides a fast, cheap and reliable research tool (Brown, 1987). Each statement in survey was ranked on a Likert scale of 1 – 5 (1 = No, never considered; 2 = No, but have considered; 3 = Yes, in progress; 4 = Yes, nearly completed; 5 = Yes, in place). All clinicians and non-clinicians (administrators) at the KATH were invited to participate in the study. Information about the study was posted on permissible notice boards of KATH.

Reliability essentially means consistent or dependable results and reliability is a part of the assessment of validity (Sullivan, 2011). In this study as with many others, it was necessary to establish reliability. The bootstrap procedure in SmartPLS3 was used in the calculation to establish reliability. Cronbach alpha calculated correlation among all the variables in every combination and a high reliability estimate should be as close to 1 as possible and generally 0.7 (Sullivan, 2011). Cronbach alpha is a test of internal consistency used to calculate the correlation values among the answers on assessment tool (Bland and Altman, 1997). In verifying the reliability of the data for this study, all questionnaire items (see Appendix 2 for description of items/measuring tools and Appendix 3, PLS algorithm output), 63 in the survey instrument were used. The value of Cronbach's alpha for the composite variables ranged from 0.903 – 0.979.

ANALYSIS AND RESULTS

Demographic information about the study participants presented in Table 1 below suggests that for gender (M = 1.56, SD = 0.497) more female, 166 (56.3%) of the 298 participated in the research compared with 129 (43.7%) male participation. For profession/position (M = 2.33, SD = 1.307) more nurses (43.6%) participated, which is a common pattern in Ghana, and in other developing countries. 88 (29%), (second largest) of Hospital administrators and management participated, which was followed by 15.4% of medical doctors. The other participating professional categories were Lab technicians and pharmacists.

For working years (M = 1.66, SD = 0.724), participants in category 1 (1-5) working years had a frequency of 144, which translates to a valid 48.8% and were the majority who participated in this research. Category 2 (6-10 years) were the second largest group to participate in this study with a valid 36.3%. In the end, 298 participated in the study.

As, Cain et al. (2016) contend, firstly we calculated the multivariate skewness and kurtosis using software available at Web Power. The result is available here at https://webpower.psychstat.org/models/kurtosis/results.php?url=84d531cdc84c85cc85724748d689b521. The output of the Mardia's multivariate suggested that the data which was collected was not multivariate normal with Mardia's multivariate skewness (β = 4.770, $p < 0.05$) and Mardia's multivariate kurtosis (β = 55.268, $p < 0.05$). Consequently, we progressed to use SmartPLS, which is a non-parametric analysis software.

Assessing overall model fit is an important problem in general structural equation models (Bollen, 1989). Schreiber et al. (2006) thought of structural equation modeling (SEM) as CFA and multiple regression because SEM is more of a confirmatory technique.

An output from the PLS Algorithm showed items with loading coefficient ranging from 0.790 to 0.884 for CR; 0.724 to 0.904 for HITR; 0.791 to 0.872 for OCR; 0.729 to 0.872 for ORR; 0.804 to 0.890 for RPR; and 0.794 to 0.889 for TR respectively.

Aspects of PLS that were used to assess reliability in reflective models include: Cronbach's alpha; Composite reliability; and Average variance extracted (AVE) (Garson, 2016). In this study, composite reliability for all constructs was high and ranged from 0.928 to 0.990 (TR=0.990; ORR=0.970; OCR=0.970; RPR=0.962; CR=0.928 and HITR=0.934), while Cronbach's Alpha ranged from 0.910 to 0.979; and average variance extracted (AVE) values ranging from 0.680 to 0.740 (see Table 2 below).

Fornell and Larcker (1981), Hair Jr et al. (2010) cited in Lee and Che (2013) posited that convergent validity, which is often used to measure the correlation of a dimension's multiple indicators, is acceptable if the following criteria are met: (i) the statistical significance of each factor loading is confirmed by a p-value of 0.05; (ii) construct reliability exceeds 0.7; and (iii) average variance extracted (AVE) is greater than 0.5. In this study, all three conditions were met as i) p-values for all factors were 0.00 ($p > 0.05$); ii) construct reliability exceeded 0.7 for all constructs; and iii) AVE ranged from 0.680 to 0.740.

Discriminant validity values ranged from 0.544 to 0.861. Validity is examined by noting a construct's convergent validity and discriminant validity (Hair Jr et al., 2014). Support is provided for convergent validity when each item has outer/indicator loadings above 0.70 (Hair Jr et al., 2014, Garson, 2016) and when each construct's AVE is 0.50 or higher (Hair Jr et al., 2014). Discriminant validity was assessed by comparing the square root of AVE for each construct to the correlation of that construct with other constructs. The AVE is the grand mean value of the squared loadings of a set of indicators (Hair Jr et al., 2016) and is equivalent to the communality of a construct.

As Garson (2016) posited, in a well-fitting model, heterotrait correlations should be smaller than monotrait correlations, implying that the HTMT ratio should be below 1.0. Henseler et al. (2015), however, suggested 0.9 as cutoff and an even stricter cutoff of 0.85 was used by Kline (2015). Consequently, discriminant validity was established between a given pair of reflective constructs in this study given that HTMT values for all pairs of reflective constructs ranged from 0.598 to 0.879 (below 1.0). HTMT values smaller than 1.0 show that the true correlation between the two constructs should differ (Alarcón and Sánchez, 2015).

The coefficient is an index to measure each endogenous latent variable's R-Square (Lee and Che, 2013). Five out of the six constructs/latent variables had R^2 with explanatory powers ranging from substantial to values above moderate, if the suggestions of Chin (1998) are anything to go by. HITR: $\boldsymbol{R^2}$ **= 0.558**; OCR: $R^2 = 0.694$; ORR: $R^2 = 0.314$; CR: $R^2 = 0.493$; and TR: $R^2 = 0.770$; and RPR (exogenous variable).

In this study, the standardized root mean square residual (SRMR) reflects the average magnitude of such differences. It is a measure of approximate fit for the researcher's model and measures the difference between the observed correlation matrix and the model-implied correlation matrix (Garson, 2016). Conventionally, a model has a good fit when SRMR is less than .08,(Hu and Bentler, 1999, Sanchez, 2013). Some researchers use the more lenient cut-off of less than .10 (Garson, 2016). The SRMR was introduced by Henseler et al. (2016) as a GoF measure for PLS-SEM in order to preclude model misspecification. Furthermore, the normed fit index (NFI) was also assessed. The NFI, which is also known as the Bentler-Bonett normed fit index,(Moss, 2009) is an incremental fit measure which computes the Chi-square value of the proposed model and relates it to a meaningful standard (Bentler and Bonett, 1980). The NFI value for this model is 0.739, which implies that this model improves the fit by 73.9% relative to the null or independence model. A model fits well if the difference between the correlation matrix implied by your model and the empirical correlation matrix should be non-significant ($p > 0.05$) (Ramayah et al., 2017). In this regard,(Henseler et al., 2016) contend that d_ULS and d_G < less than the 95% in the context of bootstrapped (See Appendix 4) quantile (HI 95% of d_G).

Given that the saturated model (measurement) fit values and the estimated model (structural model) fit values were exactly the same makes the model a saturated one with zero free paths. SRMR=0.054 (> 0.08); NFI=0.739, less than the suggested acceptance value of 0.9 (Byrne, 1994) or 0.95 (Lomax and Schumacker, 2012). While the acceptable NFI in literature is known be 0.9 or higher the fit index varies from 0 to 1 where 1 is ideal (Moss, 2009). Rules of thumb for this measure, however, recommend that models with a NFI less than 0.9 can usually be substantially improved (Bentler and Bonett, 1980) . The d_ULS < bootstrapped HI 95% of d_ULS and d_G < bootstrapped HI 95% of d_G indicating the data still fits the model well.

The f^2 of the exogenous variables with reference to Table 3 below indicate that OCR (f^2 = 0.027); ORR (f^2 = 0.028); and TR (f^2 = 0.023) had little impact on HITR at KATH. As per the threshold recommended by Cohen (1988), Chin (1998), values for f^2 between .020 and .150, between .150 and .350, and exceeding .350 indicate that an exogenous LV has a small, medium, or large effect on an endogenous LV. Consequently, f^2 values less of than 0.020 (as was the case with CR and RPR (f^2 values of 0.009 and 0.004) respectively) suggests that the two independent variables did not have any impact on the dependent variable HITR in the case of KATH. The failing f^2 values of 0.004 was unsurprising given that participants indicate in earlier interviews that a number of public healthcare facilities were going paperless despite the absence of any reliable HIT/eHealth regulatory at the national level to guide the adoption and use of various HIT/eHealth systems.

Table 2: Summary of values of model effect size *(f^2)*

	CR	HITR_	OCR	ORR	RPR	TR_
CR		**0.009**				
HITR_						
OCR	**0.161**	0.027				
ORR	**0.000**	0.027	**0.009**			**0.679**
RPR	0.026	**0.004**	0.094	**1.497**		**0.157**
TR_	**0.001**	0.023	**0.180**			

The model's $\boldsymbol{R^2}$ of **0.558** establishes that the model explains 55.8% of the total amount of variance in health information technology/eHealth readiness at KATH,(Chin, 1998, Vinzi et al., 2010), which is good. More so, the model's predictive relevance (Q^2) is assessed with a nonparametric Stone-Geisser test. Predictive relevance for the overall model is confirmed as the $Q^2 > 0$ $Q^2_{\text{Health information technology readiness (HITR)}} = 0.378$. The Q^2 values of both the full model and adjusted model (without RPR) did not change and without CR ($Q^2_{\text{Health information technology readiness (HITR)}} = 0.377$). A difference of 0.001 is an indication of the predictive accuracy of the model. The smaller the difference between predicted and original values the greater the Q^2 and thus the model's predictive accuracy (Hair Jr et al., 2014). Similarly, all endogenous constructs are confirmed as $Q^2 > 0$ $Q^2_{\text{Core Readiness (CR)}} = 0.330$; $Q^2_{\text{Organizational cultural Readiness (OCR)}} = 0.450$; $Q^2_{\text{Operational resource Readiness (ORR)}} = 0.376$; and $Q^2_{\text{Technological Readiness}} = 0.577$.

FINDINGS

The final model partially supports the hypotheses (H1, H2 and H3) of this study. Table 4 presents a summary of the results of the PLS-SEM analysis. Given that PLS-SEM estimates the measurement model and the relationships between constructs simultaneously, the significance of weights of the constructs display the significance of their impact on HIT/eHealth readiness. These weights can be interpreted similarly to the beta coefficients from a multiple regression analysis.

Observing the direction and significance of path coefficient may help in understanding the research hypotheses, whether or not are supported in the proposed model. The magnitude of this path's coefficient indicates the strength of the relationship between two independent or variable (LVs) (Urbach and Ahlemann, 2010). In this study, the bootstrap test procedure in SmartPLS was used to establish whether regression weights were significant. The standard decision dictates that a *t*-value of greater than 1.96 is significant at confidence level 95%, equivalent of $P < 0.05$. All paths coefficients appear to be significant with the strongest being between regulatory and policy readiness and operational resource readiness (RPR -> ORR) with T-statistics of 23.891. Similarly, operational resource readiness on technology readiness (ORR -> TR) was significant with T-statistics of 11.667.

Table 3: Summary of significant result testing of the structural model path coefficient

Path	Path Coefficient	Sample Mean (M)	Standard Deviation (STDEV)	T Statistics (|O/STDEV|)	P Values
CR -> HITR_	0.089	0.087	0.072	1.229	0.219
OCR -> CR	0.516	0.510	0.107	4.833	0.000
OCR -> HITR_	0.214	0.208	0.073	2.949	0.003
ORR -> CR	-0.022	-0.023	0.121	0.179	0.858
ORR -> HITR_	0.227	0.232	0.055	4.113	0.000
ORR -> OCR	0.108	0.109	0.073	1.469	0.143
ORR -> TR_	0.624	0.623	0.054	11.667	0.000
RPR -> CR	0.202	0.207	0.081	2.502	0.013
RPR -> HITR_	0.071	0.068	0.050	1.422	0.156
RPR -> OCR	0.289	0.293	0.066	4.373	0.000

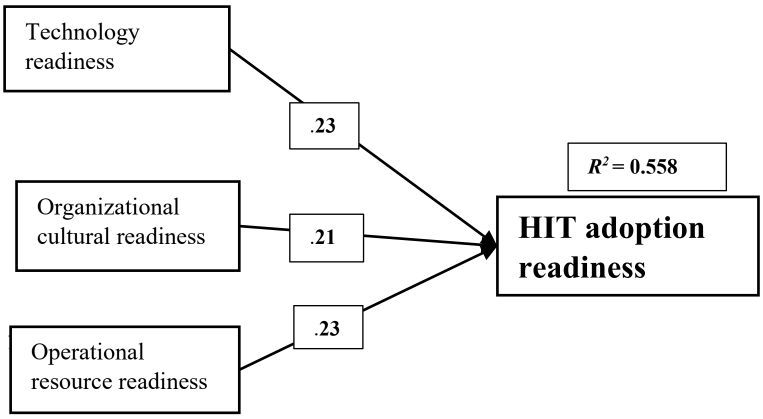
RPR -> ORR	0.774	0.773	0.032	23.891	0.000
RPR -> TR_	0.300	0.300	0.054	5.601	0.000
TR_ -> CR	0.045	0.048	0.131	0.340	0.734
TR_ -> HITR_	0.229	0.235	0.075	3.070	0.002
TR_ -> OCR	0.489	0.484	0.081	6.019	0.000

Table 4: Structural Model Hypothesis Testing

Hypothesis	Relationship	Std β	Std Error	t-Value*	Decision	F^2	Q^2	5%CI LL	95%CI UP
H1	Technology readiness -> Health Information Technology Readiness	0.229	0.075	3.070	Supported**	0.023	0.507	0.003	0.069
H2	Organizational Cultural Readiness -> Health Information Technology Readiness	0.214	0.073	2.949	Supported**	0.027	0.450	0.002	0.082
H3	Operational Resource Readiness -> Health Information Technology Readiness	0.227	0.055	4.113	Supported***	0.027	0.376	0.007	0.072
H4	Regulatory Policy Readiness Health Information Technology Readiness	0.071	0.050	1.422	Not Supported	0.004	0.000	0.000	0.021
H5	Core Readiness -> Health Information Technology Readiness	0.089	0.072	1.229	Not Supported	0.009	0.330	0.000	0.066

* Indicates Significant Path Key: * for p<.05, ** for p<.01 ***p < 0.001

Figure 3: Final and structural model assessed.



Source: Developed

DISCUSSION

In this advanced level statistical analysis the model's GoF and the research hypotheses were assessed through coefficient determination (R-Square, R^2), the standardized root mean square residual (SRMR), the path coefficient, the model effect size *(f^2)*, and the predictive relevance (Q^2) of the model. The outcome of the final model suggests support for three (H1, H2 and H3) of the five hypotheses (see Figure 3 above).

HIT/eHealth is the use of ICT in healthcare. Therefore, the availability of ICT infrastructure is a core requirement for HIT/eHealth and that has played out in this study given TR/HITR (t = 3.091), being the second among the five hypotheses. Several researches including such as Yusif and Soar (2014), Gregory and Tembo (2017), Adebesin et al. (2013) have identified the lack of ICT infrastructure as one of leading setbacks in the bid to institutionalize ICT use in healthcare in developing countries. The outcome of an early study suggests that unlike "big" teaching hospitals in "big" cities in Ghana, most public healthcare facilities in remote or rural Ghana were ICT/IT-ill-equipped to enable any successful collaboration when it comes to sharing of health information and exchange/transfer of health data electronically (Yusif et al., 2020a). This was perceived as challenge in any pursuit of eHealth adoption.

The (t = 4.053) for the path ORR to HITR was the strongest among the five, suggesting that for HIT to thrive there was the need for continuous flow of sufficient operational resources in the context of funding and health informatics trained workforce. The reality, though, is that continuous shortage of operational resources are known predicaments of HIT/eHealth in developing countries (Jalghoum et al., 2019, Omotosho et al., 2019, Zayyad and Toycan, 2018) According a related study, many eHealth initiatives in currently underway in public healthcare facilities in Ghana, like in other developing countries were being sponsored by conglomerates or external donor organizations (Yusif et al., 2020a).

The implementations of digital health systems are still in their nascent ages in developing countries and more needs to be done in understanding factors that impact on pre-implementation to help get it right during the implementation and post-implementation. These are important components of organizational cultural readiness – the ability to adapt to changes brought about new systems (Fanta et al., 2017). On the one hand, while technical issues are no strange to systems implementation, low uptake and general digital health project failures could not only be attributed to technical issues, but also organizational and human-related issues have become key determinants of digital health successes on the other hand as non-technical factors.

These factors include but are not limited to understanding acceptance issues (Al-Adwan and Berger, 2015, Landis-Lewis et al., 2015). One important partway to successful eHealth adoption/higher uptake is end-user involvement right from the start of digital health projects to bring a sense of use ownership whilst reducing any mismatch between user-system interface uptake by end-users remains a chronic challenge. For example, Van Velsen et al. (2018) found that eHealth end-user involvement can aid design teams in identifying the acceptance criteria of their eHealth application in a very early stage of the design process. User involvement not only help in user-acceptable designed system it also helps in improving users' self-efficacy in the use and maintenance of eHealth systems (Koivumäki et al., 2017).

Organizational culture (t = 2.885) equally plays an important role in ICT adoption in the healthcare environment (Zakaria et al., 2009). Similarly, Fanta and Pretorius (2018) also considered organizational composition, resources, procedures, support services, manage and improve digital health adoption process and performance as critical factors for organizational culture. Organizations with cultures that value learning and seek to encourage both individual and organizational learning are often characterized as being more organic (Bangert and Doktor, 2003). In the healthcare environment, healthcare providers have entertained fears towards adopting health information technologies as part and parcel of practices to improve healthcare delivery. Among the factors identified by Barzekar and Karami (2014) to be impacting upon the successful implementation of information technology in health systems was organizational culture featured heavily. Social influences include: subjective norm; competition; a supportive organizational culture for change, and friendship network (Li et al., 2013). The degree of a health care provider's perception of organizational culture (e.g., learning culture) helps us understand how supportive individual will be to eHealth adoption (Dansky et al., 1999). The culture of the organization, including its supportive elements, influences both the implementation and persistence of the work innovation (Dansky et al., 1999). Analysed qualitative data suggests found that change management principles and employee/stakeholder engagement including but not limited to teamwork, work climate-morale, information flow, involvement, supervision, and meetings have profound impact on eHealth readiness.

Remarkably, there was no significant relationship between core readiness and HITR. Through interviews with IT managers within participating healthcare organizations, the need for some form of strategic plan was apparent. While most of the respondents appeared to suggest the inevitability of HIT strategic plans, perhaps there was a lack of true utilization of such plans. Unlike the striking insignificant association between CR and HITR (t = 1.107). A third of respondents in the qualitative study perceived core readiness as a first step towards any eHealth readiness. The analysed quantitative data, however, suggest otherwise. This outcome could imply that practically, public healthcare facilities undertaking various eHealth initiatives may not practically have any dossier relating to eHealth strategic plans.

The outcome of an initial qualitative study suggests that many public healthcare facilities were embarking on some sorts of preliminary eHealth project in absence of any eHealth regulatory policy hence it was surprising that RPR to HITR ($t = 1.322$) was insignificant.

The strong relationships between *Regulatory Policy Readiness* and *Operational Resource Readiness* (H12) appears to suggest that funding is a prerequisite for any meaningful undertaking in any health policy (Adebayo and Ofoegbu, 2014, Scott and Mars, 2013). There is a corresponding need to look at the long-term effects that extant policies if any may have on health IT system resilience, innovation, and related ethical, social/legal issues (McGowan et al., 2012) in the context of future funding models. Furthermore, the extent to which eHealth operational resources such as availability of funds (Jaana et al., 2011, Eden et al., 2016) and experienced health informaticians (Matar and Alnabhan, 2014) were crucial for successful implementation of eHealth systems was obvious in the path of *Operational Resource Readiness* and *Technology Readiness* (H3). As indicate Gholamhosseini and Ayatollahi (2017) the issue of eHealth readiness is complex and affected by many factors, such as ICT infrastructure, policies, human skills, availability and prioritisation of funding, and managers' attitudes towards investment in ICT. Of particular interest was the path of Operational resource readiness and Technology readiness. Generally, in sub-Saharan Africa the problem of financing has been a major setback to the delivery of basic health services (Akosua and Aseweh, 2011) as well as basic ICT infrastructure (Acquah-Swanzy, 2015).

Theoretical and practical implication

Theoretically, this study makes important contributions to theory, and literature, and practice. Firstly, this study conceptualized and attributed measures to TOE variables, taking advantage of the flexible nature of the factors thereof – Technology, Organization and Environment. Most importantly, this study has made contribution to theory through confirmatory factor analysis (CFA), which enables researchers to test the hypothesis that a relationship between observed variables and their underlying latent constructs exists given that the objective of this study was to predict and explain the relationships between exogenous and endogenous constructs (Hair et al., 2017). Thus, verifying factor structure of a set of observed variables and demonstrating the advantages of second-generation (2G) statistical tool in the context of their abilities to lay bare indirect/hidden relationships and how they impact on other directional paths and ultimately on the outcome variable (Lowry and Gaskin, 2014). For example, unlike 1G or standard regression, the application of SEM (2G) further revealed that KATH did not pay enough attention to CR and RPR factors. Practically, this study contributes to the need for improved strategies for implementing ICT in the healthcare domain. This validated eHealth readiness assessment model will help to provide understanding and direction for eHealth policy development and practitioners by finding, in an evidence based manner, the most influential factors to be considered when preparing for an eHealth readiness assessment in the context of developing countries. More so, the outcome of this study provides tools for top management to relook into ICT adoption not only in healthcare organizations, but also in other industries. For example, the study demonstrates how the various directional path coefficient impact on the overall implementation process.

CONCLUSION

For effective/reliable eHealth/HIT adoption readiness assessment, there need an assessment model with an acceptance predictive accuracy. In this study, we have demonstrated the use of PLS-SEM path analysis in predicting the accuracy of an initial developed assessment model. Various paths, direct and indirect have unearthed and mapped the impact of key attributes of eHealth/HIT readiness and adoption. The model (R^2 = 0.558, Q^2 = 0.378) advocate that TR, ORR and OCR explained 55.8% of the total amount of variance in health information technology/eHealth readiness in the case of KATH. Based on the Q^2 assessment, the relevance of the overall paths of the model was predictive.

This implies that the indicators used in measuring the five independent/composite variables are reliable. Generally, the GoF for this SEM was encouraging. Given the significance association of the SEM variables, Technology readiness (TR); Operational resource readiness (ORR) and Organizational cultural readiness (OCR) on health information technology readiness (HITR), the theoretical application of the structural portion of the model, and the collective GoF indices, the SEM is considered to be a good prediction of the underlying HIT/eHealth readiness survey data. As many public healthcare organizations in Ghana have already gone paperless there is a critical need for reliable HIT/eHealth Regulatory policies (RPR) and some improvement in HIT/eHealth strategic planning (Core readiness).

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REFERENCE

ACQUAH-SWANZY, M. 2015. Evaluating Electronic Health Record Systems in Ghana: the case of Effia Nkwanta Regional Hospital.

ADEBAYO, K. & OFOEGBU, E. 2014. Issues on E-health Adoption in Nigeria. *International Journal of Modern Education and Computer Science,* 6**,** 36.

ADEBESIN, F., KOTZÉ, P., VAN GREUNEN, D. & FOSTER, R. 2013. Barriers & challenges to the adoption of E-Health standards in Africa.

AGBOKEY, F. 2014. *Health Seeking Behaviours for Breast Cancer among Breast Cancer Patients at the Komfo Anokye Teaching Hospital, Kumasi, Ghana.* University of Ghana.

AKOSUA, A. & ASEWEH, A. 2011. Financing public healthcare institutions in Ghana. *Journal of health organization and management,* 25**,** 128-141.

AL-ADWAN, A. & BERGER, H. 2015. Exploring physicians' behavioural intention toward the adoption of electronic health records: an empirical study from Jordan. *International Journal of Healthcare Technology and Management,* 15**,** 89-111.

AL SALLAKH, M., RODGERS, S., LYONS, R., SHEIKH, A. & DAVIES, G. 2017. Socioeconomic deprivation and inequalities in asthma care in Wales. *The Lancet,* 390**,** S19.

ALARCÓN, D. & SÁNCHEZ, J. 2015. Assessing convergent and discriminant validity in the ADHD-R IV rating scale: User-written commands for Average Variance Extracted (AVE), Composite Reliability (CR), and Heterotrait-Monotrait ratio of correlations (HTMT). Spanish STATA Meeting.

ALBERS, S. 2010. PLS and success factor studies in marketing. *Handbook of partial least squares***,** 409-425.

ARPACI, I. 2019. A theoretical framework for IT consumerization: factors influencing the adoption of BYOD. *Handbook of Research on Technology Integration in the Global World.* IGI Global.

BAGOZZI, R. & YI, Y. 1988. On the evaluation of structural equation models. *Journal of the academy of marketing science,* 16**,** 74-94.

BANGERT, D. & DOKTOR, R. The role of organizational culture in the management of clinical e-health systems. System Sciences, 2003. Proceedings of the 36th Annual Hawaii International Conference on, 2003. IEEE, 9 pp.

BARZEKAR, H. & KARAMI, M. 2014. Organizational factors that affect the implementation of information technology: Perspectives of middle managers in Iran. *Acta Informatica Medica,* 22**,** 325.

BEDELEY, R. & PALVIA, P. 2014. A Study of the Issues of E-Health Care in Developing Countries: The Case of Ghana.

BENTLER, P. & BONETT, D. 1980. Significance tests and goodness of fit in the analysis of covariance structures. *Psychological bulletin,* 88**,** 588.
BLAND, J. M. & ALTMAN, D. 1997. Statistics notes: Cronbach's alpha. *Bmj,* 314**,** 572.
BOLLEN, K. 1989. A new incremental fit index for general structural equation models. *Sociological Methods & Research,* 17**,** 303-316.
BROWN, S. 1987. Drop and collect surveys: a neglected research technique? *Marketing Intelligence & Planning,* 5**,** 19-23.
BYRNE, B. 1994. *Structural equation modeling with EQS and EQS/Windows: Basic concepts, applications, and programming*, Sage.
CAIN, M., ZHANG, Z. & YUAN, K. 2016. Univariate and multivariate skewness and kurtosis for measuring nonnormality: Prevalence, influence and estimation. *Behavior research methods***,** 1-20.
CHIN, W. 1998. Commentary: Issues and opinion on structural equation modeling. JSTOR.
COHEN, J. 1988. Statistical power analysis for the behavioral sciences . Hilsdale. *NJ: Lawrence Earlbaum Associates,* 2.
DANSKY, K., GAMM, L., VASEY, J. & BARSUKIEWICZ, C. 1999. Electronic medical records: are physicians ready? *Journal of Healthcare Management,* 44**,** 440-454.
DELONE, W. & MCLEAN, E. 1992. Information systems success: The quest for the dependent variable. *Information systems research,* 3**,** 60-95.
DELONE, W. & MCLEAN, E. 2003. The DeLone and McLean model of information systems success: a ten-year update. *Journal of management information systems,* 19**,** 9-30.
DELONE, W. & MCLEAN, E. 2004. Measuring e-commerce success: Applying the DeLone & McLean information systems success model. *International Journal of Electronic Commerce,* 9**,** 31-47.
DEWI, M. A. A., HIDAYANTO, A. N., PURWANDARI, B., KOSANDI, M. & BUDI, N. F. A. Smart City Readiness Model Using Technology-Organization-Environment (TOE) Framework and Its Effect on Adoption Decision. PACIS, 2018. 268.
DWIVEDI, Y., WADE, M. & SCHNEBERGER, S. 2012. *Information Systems Theory: Explaining and Predicting Our Digital Society*, Springer Science & Business Media.
EDEN, K., TOTTEN, A., KASSAKIAN, S., GORMAN, P., MCDONAGH, M., DEVINE, B., PAPPAS, M., DAEGES, M., WOODS, S. & HERSH, W. 2016. Barriers and facilitators to exchanging health information: a systematic review. *International Journal of Medical Informatics,* 88**,** 44-51.
EIGNER, I., HAMPER, A., WICKRAMASINGHE, N. & BODENDORF, F. 2019. Success factors for national eHealth strategies: a comparative analysis of the Australian and German eHealth system. *International Journal of Networking and Virtual Organisations,* 21**,** 399-424.
FABER, S., VAN GEENHUIZEN, M. & DE REUVER, M. 2017. eHealth adoption factors in medical hospitals: A focus on the Netherlands. *International journal of medical informatics,* 100**,** 77-89.
FANTA, G., PRETORIUS, L. & ERASMUS, L. 2016. A System Dynamics Model of eHealth Acceptance: A Sociotechnical Perspective. *International Association for Management of Technology IAMOT***,** 259-272.
FANTA, G., PRETORIUS, L. & ERASMUS, L. Organizational Dynamics of Sustainable eHealth Implementation: A Case Study of eHMIS. 2017 Portland

International Conference on Management of Engineering and Technology (PICMET), 2017. IEEE, 1-9.

FANTA, G. B. & PRETORIUS, L. 2018. A conceptual framework for sustainable eHealth implementation in resource-constrained settings. *South African Journal of Industrial Engineering,* 29**,** 132-147.

FORNELL, C. & LARCKER, D. 1981. Evaluating structural equation models with unobservable variables and measurement error. *Journal of marketing research***,** 39-50.

FREEZE, R., ALSHARE, K., LANE, P. & WEN, H. 2019. IS success model in e-learning context based on students' perceptions. *Journal of Information systems education,* 21**,** 4.

FRICKER, S., THÜMMLER, C. & GAVRAS, A. 2015. *Requirements engineering for digital health*, Springer.

GARSON, G. 2016. *Partital Least Sqaures: Ression & Structural Equation Models*, G. David Garson and Statistical Associates Publishing.

GEFEN, D., STRAUB, D. & BOUDREAU, M. 2000. Structural equation modeling and regression: Guidelines for research practice. *Communications of the association for information systems,* 4**,** 7.

GHOLAMHOSSEINI, L. & AYATOLLAHI, H. 2017. The design and application of an e-health readiness assessment tool. *Health Information Management Journal,* 46**,** 32-41.

GIL-GARCIA, J. 2008. Using partial least squares in digital government research. *Handbook of research on public information technology***,** 239-253.

GORLA, N., SOMERS, T. & WONG, B. 2010. Organizational impact of system quality, information quality, and service quality. *The Journal of Strategic Information Systems,* 19**,** 207-228.

GREGORY, M. & TEMBO, S. 2017. Implementation of E-health in Developing Countries Challenges and Opportunities: A Case of Zambia. *Science and Technology,* 7**,** 41-53.

GRISOT, M. & VASSILAKOPOULOU, P. 2017. Re-infrastructuring for eHealth: Dealing with turns in infrastructure development. *Computer supported cooperative work (CSCW),* 26**,** 7-31.

HAIR, J., HOLLINGSWORTH, C., RANDOLPH, A. & CHONG, A. 2017. An updated and expanded assessment of PLS-SEM in information systems research. *Industrial Management & Data Systems*.

HAIR JR, F., SARSTEDT, M., HOPKINS, L. & KUPPELWIESER, V. 2014. Partial least squares structural equation modeling (PLS-SEM): An emerging tool in business research. *European Business Review,* 26**,** 106-121.

HAIR JR, J., BLACK, W., BABIN, B. & ANDERSON, R. 2010. Multivariate Data Analysis; a global perspective (ed.): Pearson Education Inc. *New Jersey, USA***,** 5.

HAIR JR, J., HULT, G. T., RINGLE, C. & SARSTEDT, M. 2016. *A primer on partial least squares structural equation modeling (PLS-SEM)*, Sage Publications.

HAO, J., SHI, H., SHI, V. & YANG, C. 2020. Adoption of Automatic Warehousing Systems in Logistics Firms: A Technology–Organization–Environment Framework. *Sustainability,* 12**,** 5185.

HARDING, K., BIKS, G. A., ADEFRIS, M., LOEHR, J., GASHAYE, K., TILAHUN, B., VOLYNSKI, M., GARG, S., ABEBAW, Z. & DESSIE, K. 2018. A mobile health model supporting Ethiopia's eHealth strategy. *Digital medicine,* 4**,** 54.

HENSELER, J., HUBONA, G. & RAY, P. 2016. Using PLS path modeling in new technology research: updated guidelines. *Industrial management & data systems,* 116**,** 2-20.

HENSELER, J., RINGLE, C. & SARSTEDT, M. 2015. A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science,* 43**,** 115-135.

HERATH, T. C., HERATH, H. S. & D'ARCY, J. 2020. Organizational Adoption of Information Security Solutions: An Integrative Lens Based on Innovation Adoption and the Technology-Organization-Environment Framework. *ACM SIGMIS Database: the DATABASE for Advances in Information Systems,* 51**,** 12-35.

HU, L. & BENTLER, P. 1999. Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural equation modeling: a multidisciplinary journal,* 6**,** 1-55.

HUE, T. T. 2019. The determinants of innovation in Vietnamese manufacturing firms: an empirical analysis using a technology–organization–environment framework. *Eurasian Business Review,* 9**,** 247-267.

HULLAND, J. 1999. Use of partial least squares (PLS) in strategic management research: A review of four recent studies. *Strategic management journal***,** 195-204.

HUNG, S.-Y., HUNG, W.-H., TSAI, C.-A. & JIANG, S.-C. 2010. Critical factors of hospital adoption on CRM system: Organizational and information system perspectives. *Decision support systems,* 48**,** 592-603.

JAANA, M., TAMIM, H., PARÉ, G. & TEITELBAUM, M. 2011. Key IT management issues in hospitals: Results of a Delphi study in Canada. *International journal of medical informatics,* 80**,** 828-840.

JALGHOUM, Y., TAHTAMOUNI, A., KHASAWNEH, S. & AL-MADADHA, A. 2019. Challenges to healthcare information systems development: The case of Jordan. *International Journal of Healthcare Management***,** 1-9.

KLINE, R. 2015. *Principles and practice of structural equation modeling*, Guilford publications.

KOIVUMÄKI, T., PEKKARINEN, S., LAPPI, M., VÄISÄNEN, J., JUNTUNEN, J. & PIKKARAINEN, M. 2017. consumer adoption of future MyData-based preventive eHealth services: an acceptance model and survey study. *Journal of medical Internet research,* 19**,** e429.

KUPEK, E. 2006. Beyond logistic regression: structural equations modelling for binary variables and its application to investigating unobserved confounders. *BMC medical research methodology,* 6**,** 13.

KWAO, L., MILLHAM, R. & OPANIN GYAMFI, E. 2020. An Integrated Success Model for Adopting Biometric Authentication Technique for District Health Information Management System 2, Ghana. *Ghana (February 20, 2020)*.

LANDIS-LEWIS, Z., MANJOMO, R., GADABU, O., KAM, M., SIMWAKA, B., ZICKMUND, S., CHIMBWANDIRA, F., DOUGLAS, G. & JACOBSON, R. 2015. Barriers to using eHealth data for clinical performance feedback in Malawi: A case study. *International journal of medical informatics,* 84**,** 868-875.

LEE, K. & CHE, S. Introduction to Partial Least Square: Common Criteria and Practical Considerations. Advanced Materials Research, 2013. Trans Tech Publ, 1766-1769.

LENNON, M., BOUAMRANE, M.-M., DEVLIN, A., O'CONNOR, S., O'DONNELL, C., CHETTY, U., AGBAKOBA, R., BIKKER, A., GRIEVE, E. & FINCH, T. 2017. Readiness for delivering digital health at scale: lessons from a longitudinal qualitative evaluation of a national digital health innovation program in the United Kingdom. *Journal of medical Internet research,* 19**,** e42.

LI, J., TALAEI-KHOEI, A., SEALE, H., RAY, P. & MACINTYRE, C. 2013. Health care provider adoption of eHealth: systematic literature review. *Interactive Journal of Medical Research,* 2.

LIN, H.-F. 2014. Understanding the determinants of electronic supply chain management system adoption: Using the technology–organization–environment framework. *Technological Forecasting and Social Change,* 86**,** 80-92.

LOMAX, R. & SCHUMACKER, R. 2012. *A beginner's guide to structural equation modeling*, Routledge Academic New York, NY.

LONG, L.-A., PARIYO, G. & KALLANDER, K. 2018. Digital technologies for health workforce development in low-and middle-income countries: a scoping review. *Global Health: Science and Practice,* 6**,** S41-S48.

LOWRY, P. & GASKIN, J. 2014. Partial least squares (PLS) structural equation modeling (SEM) for building and testing behavioral causal theory: When to choose it and how to use it. *IEEE transactions on professional communication,* 57**,** 123-146.

LOWRY, P. & GASKIN, J. 2014 p.139. Partial least squares (PLS) structural equation modeling (SEM) for building and testing behavioral causal theory: When to choose it and how to use it. *IEEE transactions on professional communication,* 57**,** 123-146.

MATAR, N. & ALNABHAN, M. 2014. Evaluating E-Health Services and Patients Requirements in Jordanian Hospitals. *Int. Arab J. e-Technol.,* 3.

MAUNDER, K., WALTON, K., WILLIAMS, P., FERGUSON, M. & BECK, E. 2018. A framework for eHealth readiness of dietitians. *International Journal of Medical Informatics,* 115**,** 43-52.

MCGOWAN, J., CUSACK, C. & BLOOMROSEN, M. 2012. The future of health IT innovation and informatics: a report from AMIA's 2010 policy meeting. *Journal of the American Medical Informatics Association,* 19**,** 460-467.

MERTES, A. & BRÜESCH, C. Stakeholder participation in eHealth policy: a Swiss case study on the incorporation of stakeholder preferences. IRSPM 22nd Annual Conference, Edinburgh, Scotland, 11-13 April 2018, 2018. International Research Society for Public Management, 1-23.

METTLER, T. & VIMARLUND, V. Evaluation of E-Health Strategies: A Portfolio Approach. The 15th International Symposium for Health Information Management Research (ISHIMR 2011), Sept 8-9, Zurich, 2011.

MOSS, S. 2009. Fit indices for structural equation modeling. *Website: http://www. psych-it. com. au/Psychlopedia/article. asp*.

NUNNALLY, J. 1978. *Psychometric theory,* New York, McGraw-Hill.

OJO, A. 2017. Validation of the DeLone and McLean information systems success model. *Healthcare informatics research,* 23**,** 60-66.

OLIVEIRA, T. & MARTINS, M. Information technology adoption models at firm level: review of literature. European Conference on Information Management and Evaluation, 2011. Academic Conferences International Limited, 312.

OMOTOSHO, A., AYEGBA, P., EMUOYIBOFARHE, J. & MEINEL, C. 2019. Current state of ICT in healthcare delivery in developing countries. *nternational Journal of Online Engineering,* 15**,** 91-107.

PAN, M.-J. & JANG, W.-Y. 2008. Determinants of the adoption of enterprise resource planning within the technology-organization-environment framework: Taiwan's communications industry. *Journal of Computer information systems,* 48**,** 94-102.

PARTY, A. W. 2007 WP 131, 11. Working document on the processing of personal data relating to health in electronic health records (EHR). Adopted on 2007 (WP 131).

RAMAYAH, T., YEAP, J., AHMAD, N., HALIM, H. & RAHMAN, S. 2017. Testing a Confirmatory model of Facebook Usage in SmartPLS using Consistent PLS.

RIBES, D. & POLK, J. 2014. Flexibility relative to what? Change to research infrastructure. *Journal of the Association for Information Systems,* 15**,** 1.

SANCHEZ, G. 2013. PLS path modeling with R. *Berkeley: Trowchez Editions*.

SCHERER, R., SIDDIQ, F. & TONDEUR, J. 2019. The technology acceptance model (TAM): A meta-analytic structural equation modeling approach to explaining teachers' adoption of digital technology in education. *Computers & Education,* 128**,** 13-35.

SCHREIBER, J., NORA, A., STAGE, F., BARLOW, E. & KING, J. 2006. Reporting structural equation modeling and confirmatory factor analysis results: A review. *The Journal of educational research,* 99**,** 323-338.

SCOTT, R. & MARS, M. 2013. Principles and framework for eHealth strategy development. *Journal of medical Internet research,* 15.

SHIM, M. & JO, H. 2020. What quality factors matter in enhancing the perceived benefits of online health information sites? Application of the updated DeLone and McLean information systems success model. *International Journal of Medical Informatics,* 137**,** 104093.

SINGEH, F. W., ABRIZAH, A. & KIRAN, K. 2020. Bringing the digital library success factors into the realm of the technology-organization-environment framework. *The Electronic Library*.

SULLIVAN, G. 2011. A primer on the validity of assessment instruments. The Accreditation Council for Graduate Medical Education Suite 2000, 515 North State Street, Chicago, IL 60654.

SUNNY, S., PATRICK, L. & ROB, L. 2019. Impact of cultural values on technology acceptance and technology readiness. *International Journal of Hospitality Management,* 77**,** 89-96.

TEO, T., LIN, S. & LAI, K.-H. 2009. Adopters and non-adopters of e-procurement in Singapore: An empirical study. *Omega,* 37**,** 972-987.

TORNATZKY, L. & FLEISCHER, M. 1990. *The process of technology innovation,* Lexington, MA, Lexington Books.

URBACH, N. & AHLEMANN, F. 2010. Structural equation modeling in information systems research using partial least squares. *JITTA: Journal of Information Technology Theory and Application,* 11**,** 5.

VAN VELSEN, L., EVERS, M., BARA, C.-D., DEN AKKER, H., BOEREMA, S. & HERMENS, H. 2018. Understanding the acceptance of an ehealth technology in the early stages of development: An end-user walkthrough approach and two case studies. *JMIR Formative Research,* 2**,** e10474.

VEINOT, T., ANCKER, J. & BAKKEN, S. 2019. Health informatics and health equity: improving our reach and impact. *Journal of the American Medical Informatics Association,* 26**,** 689-695.

VENKATESH, V. & BALA, H. 2008. Technology acceptance model 3 and a research agenda on interventions. *Decision sciences,* 39**,** 273-315.

VINZI, V., CHIN, W., HENSELER, J. & WANG, H. 2010. Handbook of partial least squares. Springer.

WANG, C. & KU, E. 2020. eHealth in kidney care. *Nature Reviews Nephrology***,** 1-3.

WILLIAM, C. 2017. 22 Privacy and Security: Privacy of Personal eHealth Data in Low-and Middle-Income Countries. *Global Health Informatics: Principles of EHealth and MHealth to Improve Quality of Care*, 269.
WORLD HEALTH ORGANIZATION 2014. Country Coorperation Strategy Brief, Ghana. WHO.
YUSIF, S., HAFEEZ-BAIG, A. & SOAR, J. 2017a. E-health readiness assessment factors and measuring tools: a systematic review. *International journal of medical informatics,* 107, 56-64.
YUSIF, S., HAFEEZ-BAIG, A. & SOAR, J. 2017b. e-Health readiness assessment factors and measuring tools: A systematic review. *International Journal of Medical Informatics*.
YUSIF, S., HAFEEZ-BAIG, A. & SOAR, J. 2020a. An Exploratory Study of the Readiness of Public Healthcare Facilities in Developing Countries to Adopt Health Information Technology (HIT)/e-Health: the Case of Ghana. *Journal of Healthcare Informatics Research*.
YUSIF, S., HAFEEZ-BAIG, A. & SOAR, J. 2020b. A model for evaluating eHealth preparedness–a case study approach. *Transforming Government: People, Process and Policy*.
YUSIF, S. & SOAR, J. 2014. Preparedness for e-Health in developing countries: the case of Ghana. *JHIDC,* 8, 18-37.
ZAKARIA, N., YUSOF, S. & ZAKARIA, N. 2009. Managing ICT in Healthcare Organization: Culture, Challenges, and Issues of. *Handbook of Research on Advances in Health Informatics and Electronic Healthcare Applications: Global Adoption and Impact of Information Communication Technologies: Global Adoption and Impact of Information Communication Technologies,* 153.
ZAYYAD, M. & TOYCAN, M. 2018. Factors affecting sustainable adoption of e-health technology in developing countries: an exploratory survey of Nigerian hospitals from the perspective of healthcare professionals. *PeerJ,* 6, e4436.

Appendix 1: Qualitative research sample

	Distribution of sample	Location	Sample	No. Invited	No. Participated
1	20 eHealth projects	Accra	Project leaders/Managers	20	2
2	37 Military Hospital		Head of IT	1	1
3	NITA	Accra	Head of IT, Head of applications and Director General	3	1
4	eGovernment Ghana (MOC)	Accra	Coordinator	1	1
5	MOH	Accra	HIT coordinator	1	1
6	GHS	Accra	Head of IT, Administrative Manager	2	2
7	SPH (Dept of Health informatics)	UG	lecturers	3	1
8	NHIS	Accra	Director of information management	1	1
9	Korle Bu Teaching Hospital	Accra	Head of IT, Senior Admin officer	2	1
10	Komfo Anokyi Teaching Hospital	Kumasi	Head of IT, Senior Admin officer	2	2
			Total	**36**	**13**

Appendix 2: Quantitative research sample

Distribution of sample	Location	Sample	N0.	No. Participated
Komfo Anokyi Teaching Hospital	Kumasi	Doctors	500	49
		Nurses/Lab Tech	2000	158
		Administrators	300	91
Total			2800	298

Table 1: Construct reliability and validity

Constructs	Items	Loadings[a]	Cronbach α[b]	AVE[c]	CR[d]
CR: Core readiness	CR1	**0.793**	**0.903**	**0.721**	**0.928**
	CR2	**0.888**			
	CR3	**0.884**			
	CR4	**0.824**			
	CR5	**0.853**			
HITR: Health information tech. readiness	HITR1	**0.715**	**0.910**	**0.739**	**0.934**
	HITR2	**0.911**			
	HITR3	**0.859**			
	HITR4	**0.890**			
	HITR5	**0.908**			
OCR: Organizational cultural readiness	OCR1	**0.843**	**0.967**	**0.698**	**0.970**
	OCR2	**0.837**			
	OCR3	**0.819**			
	OCR4	**0.835**			
	OCR5	**0.846**			
	OCR6	**0.855**			
	OCR7	**0.809**			
	OCR8	**0.797**			
	OCR9	**0.842**			
	OCR10	**0.796**			
	OCR11	**0.839**			
	OCR12	**0.854**			
	OCR13	**0.850**			
	OCR14	**0.870**			
ORR: Operational resource readiness	ORR1	**0.860**	**0.966**	**0.680**	**0.970**
	ORR2	**0.867**			

	ORR3	**0.856**			
	ORR4	**0.853**			
	ORR5	**0.842**			
	ORR6	**0.845**			
	ORR7	**0.851**			
	ORR8	**0.847**			
	ORR9	**0.864**			
	ORR10	**0.776**			
	ORR11	**0.792**			
	ORR12	**0.737**			
	ORR13	**0.89**			
	ORR14	**0.753**			
	ORR15	**0.783**			
RPR: Regulatory policy readiness	RPR1	**0.861**	**0.956**	**0.740**	**0.962**
	RPR2	**0.878**			
	RPR3	**0.862**			
	RPR4	**0.865**			
	RPR5	**0.891**			
	RPR6	**0.881**			
	RPR7	**0.862**			
	RPR8	**0.798**			
	RPR9	**0.844**			
TR: Technology readiness	TR1	**0.794**	**0.979**	**0.711**	**0.980**
	TR2	**0.845**			
	TR3	**0.813**			
	TR4	**0.798**			
	TR5	**0.793**			
	TR6	**0.846**			
	TR7	**0.851**			
	TR8	**0.847**			

TR9	**0.834**
TR10	**0.846**
TR11	**0.842**
TR12	**0.869**
TR13	**0.835**
TR14	**0.845**
TR15	**0.888**
TR16	**0.872**
TR17	**0.870**
TR18	**0.868**
TR19	**0.860**
TR20	**0.840**

a. All item loadings > 0.4 indicates Indicator reliability Hulland (1999)

b. All Cronbach's Alpha > indicates Indicator Reliability Nunnally (1978)

c. All Average Variance Extracted (AVE) > 0.5 indicates Convergent Reliability Bagozzi and Yi (1988), Fornell and Larcker (1981)

d. All Composite reliability (CR) > 0.7 indicates Internal Consistency Gefen et al. (2000)

Appendix 2: Full description of measuring tools for readiness assessment factors

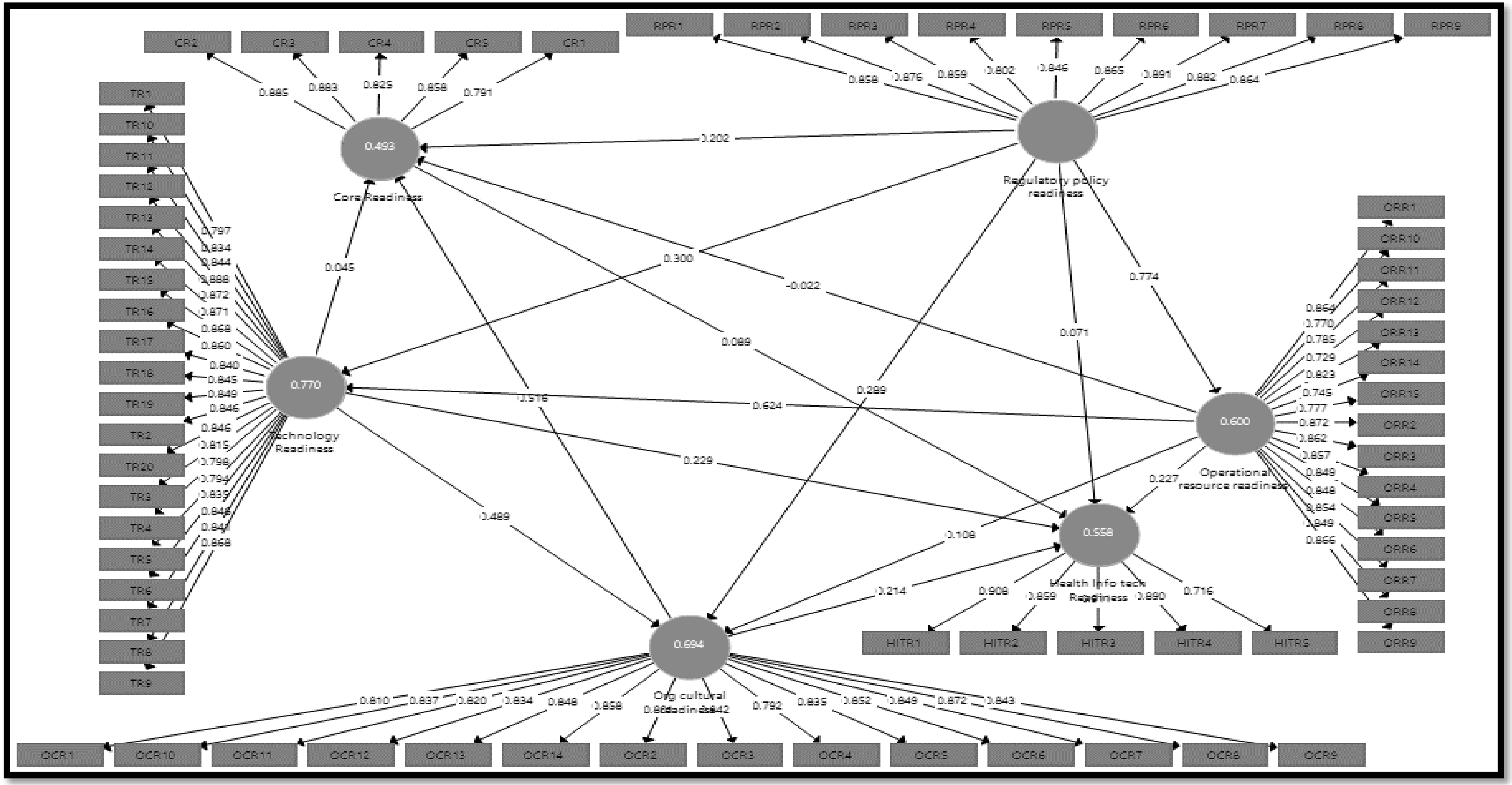
Item	**Description**	**CR**	**HITR**	**OCR**	**ORR**	**RPR**	**TR**
CR1	An official document outlining HIT implementation plan is in place.	**.817**					
CR2	A need assessment including special health characteristics and needs of the population has been performed.	**.801**					

CR3	HIT supported services have been determined.	**.738**					
CR4	Staff with relevant knowledge/skills are available.	**.729**					
CR5	Evidence on the practical effectiveness of HIT and lessons learned has been drawn	**.703**					
HITR1	In the context of Core Readiness (CR) for HIT we are ready		**.715**				
HITR2	In the context of Organizational Cultural Readiness (OCR) for HIT we are ready		**.911**				
HITR3	In the context of Operational Resource Readiness (ORR) for HIT we are ready		**.859**				
HITR4	In the context of Regulatory Policy Readiness (RPR) for HIT we are ready		**.890**				
HITR5	In the context of Technological Readiness (TR) for HIT we are ready		**.908**				
OCR1	End users (doctors, nurses, administrators) are being consulted throughout the HIT pre-implementation process			**.733**			
OCR2	The hospital has established process used engaging all stakeholders.			**.728**			
OCR3	The hospital has identified other interested hospitals collaborators.			**.723**			
OCR4	The HIT initiative has been supported by members of the board of directors			**.711**			
OCR5	The HIT initiative has been supported by management leadership			**.695**			
OCR6	All relevant champions have been identified			**.684**			
OCR7	Reliable communication channels have been established			**.669**			
OCR8	There are plans for creating awareness			**.659**			
OCR9	All relevant stakeholders have been participating in all relevant implementation plans			**.625**			
OCR10	The hospital has successfully implemented related systems previously			**.603**			
OCR11	Leaders to foster change management among all stakeholders have been identified and they are known			**.601**			
OCR12	All relevant change management teams have been put in place and they are known			**.601**			
OCR13	There are plans to manage/deal with anticipated changes to be brought about by the HIT system deployment			**.600**			
OCR14	There are measures in place to collect and evaluate feedback from users			**.598**			
ORR1	The hospital has conducted analysis on the cost/benefit of using HIT services.				**.772**		
ORR2	Relevant tools for HIT usage for both care providers and care receivers/patients have been identified				**.748**		
ORR3	Continued costs of operating the system have been projected/determined.				**.746**		
ORR4	Situations have been developed to test repayment of services delivered through HIT.				**.732**		

ORR5	The hospital has determined any projected return/savings on the investment				**.723**		
ORR6	The hospital has investigated which services have been covered by the National Health Insurance (NHI) can be delivered by eHealth technologies				**.706**		
ORR7	Issues of payment for services delivered through HIT have been resolved				**.695**		
ORR8	Issues of eligibility requirement for repayment by NHIS has been determined				**.666**		
ORR9	The hospital has determined the availability of the system (sites) for both the general public and care providers				**.649**		
ORR10	There are enough skills to successfully implement the HIT system				**.648**		
ORR11	Individual and collective roles have been determined				**.648**		
ORR12	IT staff are happy to implement the system				**.644**		
ORR13	The is a reasonable level of acceptance among users				**.640**		
ORR14	Plans are in place to train staff on using the HIT technology to be implemented.				**.638**		
ORR15	The hospital has conducted analysis on the cost or benefit of using HIT services.				**.627**		
RPR1	Issues of liability in the use of the technology has been determined					**.750**	
RPR2	The selected eHealth services conform to the NHIS covered scheme/services					**.737**	
RPR3	There is available guideline on the use of the technology					**.711**	
RPR4	Measures are in place to conform to changing HIT regulations					**.708**	
RPR5	Points (sites) of HIT services identified and requirements being examined.					**.665**	
RPR6	The chosen HIT to be implemented meet the regulatory framework available					**.626**	
RPR7	There are regulation permitting the use of the chosen technology					**.622**	
RPR8	The chosen HIT practices are in line with information protection acts					**.604**	
RPR9	Patient electronic data protection measures are in place					**.561**	
TR1	The types of HIT have been scrutinized, in terms of the functionalities.						**.766**
TR2	The hospital has identified the medical requirements that have to be met using the HIT.						**.746**
TR3	The practical viability of the selected HIT has been considered, such as user friendliness of the system for both patients/providers.						**.735**
TR4	The hospital has assessed the need of the HIT for the serving population						**.730**
TR5	The hospital has examined the HIT to be implemented in the context of workflow improvement/simplification.						**.728**
TR6	The chosen HIT is interoperable with existing systems in the hospital and being examined in the context of other healthcare facilities/agencies.						**.714**

TR7	The availability of reliable Internet has been determined.						**.712**
TR8	The hardware and software required for the selected HIT technology is available for purchase.						**.712**
TR9	The cost of the hardware and software required for the selected HIT technology would be reasonable						**.708**
TR10	The service delivery technology/device has been discussed/selected/purchased and tested.						**.704**
TR11	The service delivery technology/device will meet the hospital’s needs for delivering client/patient services.						**.698**
TR12	Issues of HIT system quality have been discussed/resolved.						**.677**
TR13	Issues of HIT information quality have been discussed/resolved.						**.671**
TR14	Issues of HIT service quality have been discussed/resolved						**.664**
TR15	Issues of HIT system use have discussed/resolved						**.664**
TR16	Issues of user satisfaction have been discussed/resolved						**.630**
TR17	Information about deployment plans has be made known to relevant stakeholders.						**.623**
TR18	The hospital has determined when the system would be implemented.						**.612**
TR19	A training session for end-users on using the HIT technology is in place.						**.609**
TR20	There is a plan to keep stakeholders informed on the progress of the system deployment.						**.596**

Appendix 3: PLS ouput showing outerloadings for indicators



Appendix 4: PLS3 Output showing t-statistics from bootstrapping procedure