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A task-fit measure of health information technology use

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Abstract

Rationale, aims and objectives: Introducing profession concerns into the evaluation of health information technology (HIT) use is an important and developing practice. A comprehensive evaluation should include the intellect elements of HIT use. This paper proposes a task-fit measure of HIT that integrates an information/knowledge quality scale into a validated judicious HIT use measure. It also presents some statistics that have implications for policy-making and curriculum development.

Methods: Statistical analyses were performed on a subset of survey data. A structural equation modelling technique was applied to examine the associations among intent to use HIT, professional concerns and information/knowledge quality.

Results: The statistical results show that altruism, autonomy, physician-patient relationship, (subconscious) autonomy, digestible information and medical history associate with each other to different extents. Only altruism and medical history show to be significant determinants of intent to use at $p<0.001$ and $p<0.05$ respectively. The scaled χ^2 difference test shows that this model is not significantly different from the judicious HIT use model.

Conclusion: The statistical results suggest that professional concerns, digestible information and person-related information are HIT use decision factors. Perhaps physicians may prefer HITs considered to be compatible with practising the science, humanism and ethics of medicine simultaneously. This research direction will potentially contribute to identifying the task-fit HITs and the corresponding policies for re-orientating medicine to be a science-using and compassionate practice in this eHealth era, thereby promoting the development of person-centered healthcare.

Keywords

Attitude to computer, clinical reasoning, ethics, humanism, information policy-making, knowledge use/utilization, medical informatics, person-centered healthcare

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Introduction

Medicine has historically been regarded as a science-using and compassionate practice [1-4]. In recent decades, however, the advent of evidence-based medicine (EBM) movement and the rapid development of health information technology (HIT), have resulted in physicians practicing in an information-overloaded environment [5], being expected to search for the best and most current strategies of care from enormous amounts of clinical data [5,6]. Consequently, time for interacting with patients is shortened [6] in both relative and absolute terms. If this issue is not mitigated, medicine will more and more become a practice characterised by the technical application of procedures, with physicians unable to care for and about the persons in need of care.

Some authors have suggested that HIT can help in the re-humanising of medicine if the capacities of HIT can be enhanced and properly utilised to process person-related information [4,7]. An oft-cited theory asserts that, for an IT to have a positive impact on individual performance, it must have a good fit with the tasks it supports [8]. Designing task-fit measures of HIT use therefore appears a rational and urgent way forward.

Recently, introducing professional concerns into the evaluation of HIT use has been proposed [9,10]. Since medical practice is an intellectual, human and moral exercise [4], clinical reasoning draws upon a gamut of factors as part of diagnosis and decision-making [11]. Development must therefore include such elements. An oft-cited paper shows that information quality - inherent usefulness of information - impacts decision effectiveness positively [12]. A task-fit measure of HIT use may be built on this idea.

Effective clinical decision-making requires knowing when, how and in what ways to apply tacit and experiential knowledge as well as a range of other sources of ‘knowing’ in medicine into patient care [7]. A purpose of implementing eHealth is to allow easy access to patient data across the nation or continent [13,14]. Clinical reasoning becomes a process that involves transforming patient data into a dimension of knowledge that is

Table 1 Summary of the sample references†

Construct	Sample support references
Information/knowledge quality	
Complete guidelines	• A system may include guidelines in diagnostic levels and types, drug dosage (medication formulary), treatments and preventive services [20].
Completeness of patient data	• Patient data should include patient history, clinical context information [21] and patient narrative [22].
Conciseness	• Clinicians and researchers are working in a 'data overload' environment [23].
Consistency	• Information should accord with physicians' experiential and tacit knowledge [21].
Format	• Guidelines do not have to be prescriptive, but need to be in user-friendly presentation [21].
Understandability	• A system should use standardised terminology/medical vocabulary used both within and across natural language communities [24].

† The literature search was conducted according to 2 propositions: (1) information quality may consist of accuracy, timeliness, completeness, relevance, and consistency [25]; (2) a purpose of applying HIT for consultation is to support implementing guideline-adherent decisions [23,26].

applicable to patient care. Patient data *per se* are information, as they are embedded in a context of relevance to the recipient (cf [15]). There exist HITs that can process tacit knowledge to some extent [6]. These capacities will likely be progressively enhanced [6]. However advanced, HITs *per se* will never be a substitute for clinical reasoning [6]. It requires physicians faithfully to apply their practical wisdom to process and act on the coded knowledge as if they were 'the' patients.

This paper proposes an information/knowledge quality scale to estimate the intellect elements of HIT use. It will be integrated with a previously validated measure of judicious HIT use [9] to form a task-fit measure. The subsequent section will outline the process of model formulation, operationalisation and statistical analysis. The results section will present a validated model and some statistics that have implications for curriculum development. In the concluding section, implications and further research directions will be discussed.

Methods

Design

The data are a subset of survey data collected by a questionnaire designed to develop an eHealth success model. A questionnaire has been a popular method for information system research for decades [16].

Each construct was defined by the stylised facts collected from a sample of publications. Table 1 summarises the stylised facts that define the information/knowledge quality construct (*iKnowQ*). The summary of intent to use HIT for consultation (*Intent2Use*) and physician attributes (*PhyAttr*) is available at Tsang [9]. The survey instrument was primarily developed by combining the scales from some standard measures with established reliability and validity [17]. Some items were developed based on findings of the relevant literature [18] when no appropriate measure could be identified [19]. Appendix I presents the 39 items that operationalised the 3 constructs - *Intent2Use*, *PhyAttr* and *iKnowQ*.

The contact information was collected from PubMed. Programmes written by the author in Visual Basic for Applications (http://en.wikipedia.org/wiki/Visual_Basic_for _Applications) were applied to select 1,000 potential candidates who were likely to be physicians working in the public hospitals of Andalusia and Madrid. Computer-assisted telephone interviews were conducted based on the translated instrument during April 2010. The survey company contacted 866 physicians and 219 of them answered at least one question. So, the response rate was 25.29%. Discarding responses when only a few questions have been answered is a recommended approach [27]. Statistical analyses were performed on the responses from 205 interviewees who answered at least half of the questionnaire.

Statistical analysis

The statistical analyses were performed by a freeware R version 2.15.0 [28] and largely by 2 packages: psych version 1.1.12 [29] and lavaan version 0.4-13 [30]. Imputation was performed by mice version 1.0 [31]. The analysis involved testing the data structure, imputation, dimension reduction and structural equation modelling (SEM).

First, the Mardia test showed that the multivariate normality assumption was violated (with p=0 for skew and kurtosis). Second, predictive mean matching (PMM) imputation was applied to fill in the 324 item-nonresponses (4.05%) once. The inferences of PMM tend to be robust to minor departures from the multivariate normality assumption [32]. Third, principal factor analysis was performed on each construct. Numbers of subfactors to extract were determined by parallel analyses [33]. Varimax rotation was also performed. Any item loaded insignificantly (with magnitude smaller than 0.40) or with significant cross-loading was dropped iteratively [34]. A subfactor would be discarded if its explained variance was smaller than 0.10 [35], its eigenvalue was smaller than 1

[36] or it had only one significant indicator [33]. Fourth, Cronbach's [37] alpha (α) reliability tests were performed on each subfactor. Items might be eliminated iteratively to obtain 0.60 α level - the minimum acceptable level for research in an exploratory mode [38]. Items with low corrected item-total correlations (<0.40) would also be eliminated [39]. Fifth, Satorra-Bentler (SB) scaled statistics [40] was the chosen SEM procedure. It is a good general approach to adjust both the unreliable standard errors and fit indices due to non-normality when sample size is equal to or greater than 200 [41]. An iterative process was applied to eliminate paths with insignificant z at $p<0.05$ [36]. Model re-specification was performed if indicated by the modification indices. This is often a necessary procedure [42]. This SEM process was also performed to re-examine Tsang's [9] model. Scaled χ^2 difference test were performed to compare the fits of the 2 models.

Results

Physician characteristics

The gender ratio (Male:Female) is 55.1:40. About 57.5% (56.1%) of the male (female) respondents claimed that HIT training was in their medical school curriculum. The overall rate is 56.9%. In fact, the observation that practitioners are not well prepared for using HIT has been a concern [5]. The non-frequent user to frequent user ratio of female respondents is 2.4:90.2, but that of male respondents is 9.7:85. Some evidence does suggest that females have a more positive attitude toward computers [43]. HIT training positively correlates with 7 *iKnowQ* items, the 4 user satisfaction items, frequency of use and *itU*2 significantly either at $p<0.05$ or $p<0.01$. HIT training is shown to have some positive impact on user satisfaction and HIT adoption. Items *iKQ*2, *iKQ*3, *iKQ*4 and *itU*1 correlate with practice experience negatively and significantly at either $p<0.05$ or $p<0.01$. The more experienced physicians showed less satisfaction with the digestibility of the information and less dependence on HIT for consultation. Further details are available elsewhere [9,10].

Data reduction

The exploratory factor analyses recommended extracting 2 *Intent2Use* subfactors, 4 *PhyAttr* subfactors and 2 *iKnowQ* subfactors. The Cronbach [37] reliability tests suggested eliminating a 3-item *Intent2Use* subfactor whose α score was 0.54. The α scores of the 7 validated subfactors ranged from 0.68 to 0.83 intent to use (*itU*), α=0.68; altruism (*Altruism*), α=0.69; autonomy (*Autonomy*), α=0.79; physician-patient relationship (*Pat.Rel*), α=0.71; (subconscious) autonomy (*Sub.Auto*), α=0.69; digestible information (*iDigest*), α=0.83 and medical history (*Med.Hist*), α=0.76. The validated subfactors were submitted to perform SEMs.

Structural equation modelling

A task-fit measure

Table 2 and Figure 1 illustrate the validated model. The modelling process involved eliminating the *pa*13 item (*pa*13 ← *Pat.Rel* with modification index 18.66). It was performed to improve the fit and interpretability of the *Sub.Auto* subfactor (interpretability is important for determining factor structure [33]). It demonstrated convergent validity, as all the z values were significant at least at $p<0.05$ [44]. Discriminant validity was also demonstrated, as none of the factor correlations was greater than $|1|$ after substracting (or adding) 1.96* standard error [45]. So, it fulfils the minimum requirements to establish construct validity [36]. The 4 *PhyAttr* subfactors associated with each other at least at $p<0.01$. *Sub.Auto* and *Altruism* associated with *iDigest* and *Med.Hist* at least at $p<0.05$. *Pat.Rel* and *iDigest* associated with *Med.Hist* at $p<0.01$ and $p<0.001$ respectively. Only *Altruism* and *Med.Hist* were demonstrated to be significant determinants of *itU* at $p<0.001$ and $p<0.05$ respectively.

Table 2 also details the fit indices. The SB scaling correction factor was 1.044. So, the maximum likelihood χ^2 was overstated approximately by 4.4%. The p-value of SBχ^2 was 0.03. The p-value of Swain corrected SBχ^2 was 0.071 - a recommended procedure for performing SEM on a relatively small sample [46]. So, this model may not be rejected. Particularly, it fulfils the double fit criteria [47]. CFI (comparative fit index) and TLI (Tucker-Lewis index) surpassed 0.95, and SRMR (standardised root mean residual) was smaller than 0.09 [47]. RMSEA (root mean square error of approximation) smaller than 0.05 may indicate 'very good' fit [48]. The data appear to fit the model extremely well.

Comparison

Figure 2 shows the refined judicious use model (Model 2). The fit indices were SBχ^2=118.714, df=98, p=0.076, CFI=0.97, TLI=0.968, RMSEA=0.032 and SRMR=0.06. The 4 *PhyAttr* subfactors associated with each other significantly at least at $P<0.05$, in the greater number of cases at $P<0.001$. *Altruism* was the sole significant determinant of *itU* at $P<0.001$. The quantitative results were slightly different from those presented in Tsang [10], as a different subset of data was used.

The scaled χ^2 difference test was performed. The fit of Model 1 is not significantly different from that of Model 2 ($\Delta\chi^2$=116.22, Δdf=98 and p=0.101). A task-fit model that includes 2 perceived net benefits subfactors was also validated. However, Model 1 appears to be a more parsimonious and better-fitted measure. Further detail is available from the author on request.

Table 2 Intent to use HIT, physician attributes and information/knowledge quality

Fit statistics†		χ^2	df	Pr(>χ^2)	RMSEA‡	SRMR	TLI	CFI
Satorra-Bentler scaled (SB)		234.959	196	0.030	0.031	0.062	0.964	0.966
Swain-corrected (SC)		225.819	196	0.071	0.027	–	0.972	0.974
ItU-PhyAttr-iKQ (model 1)								

	Estimate	Std. error	*z* value	Pr(>|*z*|)	95% CI	
Path statistics						
pa9←Autonomy	0.8127	0.0522	15.5530	0.0000 ***	0.7103	0.9151
pa10←Autonomy	0.7037	0.0599	11.7404	0.0000 ***	0.5863	0.8212
pa11←Autonomy	0.7187	0.0603	11.9252	0.0000 ***	0.6006	0.8368
pa5←Pat.Rel	0.6143	0.0736	8.3518	0.0000 ***	0.4701	0.7584
pa6←Pat.Rel	0.4979	0.0684	7.2823	0.0000 ***	0.3639	0.6319
pa8←Pat.Rel	0.7673	0.0595	12.8853	0.0000 ***	0.6506	0.8840
pa15←Pat.Rel	0.6043	0.0680	8.8868	0.0000 ***	0.4710	0.7376
pa12←Sub.Auto	0.7952	0.0880	9.0399	0.0000 ***	0.6228	0.9676
pa19←Sub.Auto	0.4665	0.0742	6.2857	0.0000 ***	0.3210	0.6119
pa1←Altruism	0.6612	0.0862	7.6686	0.0000 ***	0.4922	0.8302
pa2←Altruism	0.7322	0.0633	11.5730	0.0000 ***	0.6082	0.8562
pa4←Altruism	0.5649	0.0588	9.5996	0.0000 ***	0.4495	0.6802
iKQ2←iDigest	0.7784	0.0698	11.1462	0.0000 ***	0.6415	0.9153
iKQ3←iDigest	0.8282	0.0819	10.1184	0.0000 ***	0.6677	0.9886
iKQ4←iDigest	0.7528	0.0667	11.2873	0.0000 ***	0.6221	0.8835
iKQ6←Med.Hist	0.7447	0.0571	13.0471	0.0000 ***	0.6329	0.8566
iKQ7←Med.Hist	0.7466	0.0601	12.4227	0.0000 ***	0.6288	0.8644
iKQ8←Med.Hist	0.6535	0.0615	10.6287	0.0000 ***	0.5330	0.7740
itU1←itU	0.5133	0.0635	8.0787	0.0000 ***	0.3887	0.6378
itU2←itU	0.5217	0.0628	8.3060	0.0000 ***	0.3986	0.6449
itU3←itU	0.4084	0.0577	7.0772	0.0000 ***	0.2953	0.5215
itU←Altruism	0.7689	0.1674	4.5923	0.0000 ***	0.4407	1.0971
itU←Med.Hist	0.2888	0.1377	2.0965	0.0360 *	0.0188	0.5587
Autonomy↔Pat.Rel	0.4705	0.0815	5.7727	0.0000 ***	0.3108	0.6303
Autonomy↔Sub.Auto	0.3346	0.0845	3.9613	0.0001 ***	0.1690	0.5001
Autonomy↔Altruism	0.2080	0.0730	2.8507	0.0044 **	0.0650	0.3511
Pat.Rel↔Sub.Auto	0.4096	0.0856	4.7834	0.0000 ***	0.2417	0.5774
Pat.Rel↔Altruism	0.2165	0.0815	2.6558	0.0079 **	0.0567	0.3762
Pat.Rel↔Med.Hist	0.1658	0.0635	2.6121	0.0090 **	0.0414	0.2901
Sub.Auto↔Altruism	0.5253	0.0890	5.9050	0.0000 ***	0.3509	0.6996
Sub.Auto↔iDigest	0.2016	0.0830	2.4301	0.0151 *	0.0390	0.3643
Sub.Auto↔Med.Hist	0.4094	0.0938	4.3641	0.0000 ***	0.2255	0.5933
Altruism↔iDigest	0.4178	0.0702	5.9499	0.0000 ***	0.2802	0.5555
Altruism↔Med.Hist	0.3588	0.0808	4.4401	0.0000 ***	0.2004	0.5171
iDigest↔Med.Hist	0.4652	0.0639	7.2781	0.0000 ***	0.3400	0.5906

* indicates significance at p<0.05, ** at p<0.01 and *** at p<0.001.
†SB scaling correction factor: 1.044; SC scaling factor: 0.961.
‡SB RMSEA 90% CI: (0.011, 0.045); SC RMSEA 90% CI: (0, 0.042).
df, degrees of freedom; RMSEA, root mean square error of approximation; SRMR, standardized root mean residual; TLI, Tucker-Lewis index; CFI, comparative fit index.

Discussion

This paper proposes an alternative measure of HIT use (Model 1). Statistical analyses were performed on a subset of survey data collected from public hospital physicians. The structural equation modelling technique was applied to derive a regression model of intent to use HIT on professional concerns and information/knowledge quality. *Altruism* and *Med.Hist* are shown to be significant determinants of *itU* at p<0.001 and p<0.05 respectively. Other subfactors associate with each other to different extents. The scaled χ^2 difference test shows that Model 1 is not significantly different from the judicious use HIT measure (Model 2). In theory, epistemological elements and professional concerns are essences of clinical reasoning [49]. In this respect, Model 1 may be a more comprehensive measure. Further research is needed to confirm which model is the preferred measure.

In future research, information overload should be an explicitly area of study. Overload is a factor which signals that HIT fails to facilitate the practice. It also manifests dysfunctions that mentally exhaust individuals and cause long-term or chronic stress similar to burnout [50]. Medical practice is an intellectual, human and moral exercise [4]. This demanding task cannot be accomplished by mentally exhausted and burnt out individuals. Addressing this issue will help physicians adopt HIT into their routine practice sooner and in a healthier manner.

Medicine has historically been characterized as a science-using and compassionate practice [1-4]. Sadly and as Miles has pointed out, some evidence suggests that today’s practitioners are wary of introducing empathetic and compassionate approaches into their care even when

Figure 1 Path diagram - Physician attributes, information/knowledge quality and intent to use HIT (Model 1)

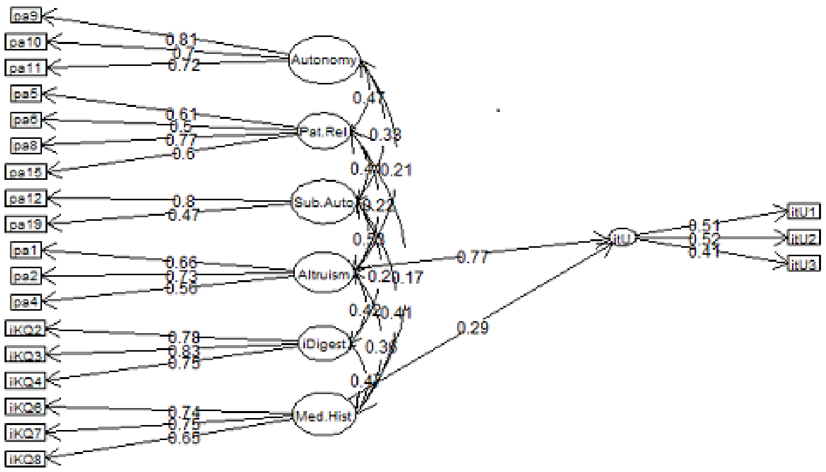
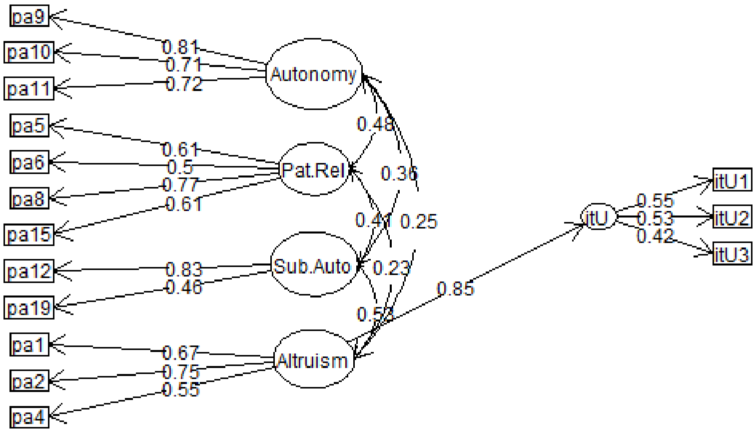


Figure 2 **Path Diagram – Intent to use HIT and physician attributes (Model 2)**



there is adequate time and opportunity to do so [4]. Informatics design can have a role in re-orientating medicine and this paper shows that humanistic factors can be quantified. Professional concerns, digestible information and person-related information are shown to be HIT use decision factors. Systems that can process person-related information are considered to be compatible with practising models of medicine that care for patients as whole persons [4]. It is asserted that research of this type has the potential to contribute to a reconnection of the science, humanism and ethics of medicine through designing task-fit HITs and their corresponding policies.

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Appendix

a.1 Intent to Use

itU1 I am dependent on the system for my consultations.
itU2 I always use the system to record patients' medical records.
itU3 I always use the system to assist my clinical decisions including diagnoses, therapies and referrals.
itU4 I use the system as much as possible to communicate or coordinate with my colleagues.
itU5 I usually get the laboratory results *via* the system.
itU6 I often use the Internet to search for information.
itU7 Overall, I use the system as much as possible.

a.2 Physician Attributes

pa1 I use the system as my Department/Centre will perform better.
pa2 I use the system as it helps improve patient satisfaction with care.
pa3 I use the system as the top management sees the system as being important.
pa4 I use the system as patients tend to prefer my using a computer.
pa5 I pay less attention to patients after using the system.
pa6 My attention is focused on the chart/computer.
pa7 I can still spend enough time with patients.
pa8 The system interferes my relationships with patients.
pa9 I need to communicate with my colleagues or supervisor more.
pa10 I need the help of my colleagues more.
pa11 I need to consult my colleagues or supervisor more often before making decisions for non-routine (or uncommon) cases.
pa12 My performance will be more closely monitored.
pa13 I have more control over my job.
pa14 The system allows me to treat patients as individuals.
pa15 The system adversely affects my independence and freedom in how I deliver patient care.
pa16 It is a professional ethic to treat each patient as an individual.
pa17 I usually take patient preference into consideration when I make a clinical decision.
pa18 An understandable medical record should include clinical contextual information.
pa19 I am more aware of the legal liability after the system has been implemented.

a.3 Information/knowledge quality

iKQ1 Information from the system is not concise enough.
iKQ2 Information from the system appears to be readable, clear and well formatted
iKQ3 Information from the system uses terminology or vocabulary that is easy to understand.
iKQ4 Information from the system is generally in a readily usable form.
iKQ5 The system contains essential patients' demographic information.
iKQ6 Patient data from the system usually include complete patient problem lists.
iKQ7 Patient data from the system usually include complete electronic lists of medications taken by patients.
iKQ8 Patients' medical histories from the system are usually detailed enough.
iKQ9 Patient data from the system usually include essential clinical context information.
iKQ10 Patient data from the system include patient narrative about patients' experience and opinions.
iKQ11 I can retrieve laboratory results from the system.
iKQ12 Patient follow-up notes from the system are usually detailed enough.
iKQ13 The system generally provides reports, reminders or alerts that seem to be exactly what are needed.

† The 26 items that operationalise the intent to use and physician attributes constructs have been published in Tsang [9,10]. The Spanish version is available on request.
‡ The responses are on a 7-point Likert scale (1 = Strongly Disagree; 2 = Disagree; 3 = Moderately Disagree; 4 = No Opinion or Uncertain; 5 = Moderately Agree; 6 = Agree; 7 = Strongly Agree).