ARTICLE

Health information technology use and the decisions of altruistic physicians

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Abstract

Rationale, aims and objectives: Knowledge is the basis and mediator of medical care. Health information technology (HIT) can help in improving care only if physicians faithfully apply their knowledge during its use. A measure of judicious HIT use has recently been proposed. Behavioural research and the oft-cited technology acceptance model suggest that beliefs/perceptions may also represent decision factors. This paper proposes a perception scale and an alternative measure of judicious HIT use.

Methods: Statistical analyses were performed on a subset of survey data collected for developing an eHealth success model. This paper focuses on deriving a structural equation model that can explain the associations among intent to use HIT, professional concerns and perceptions about the impacts of HIT on care benefits.

Results: The statistical results show that altruism, autonomy, the physician-patient relationship, (subconscious) autonomy, efficiency and efficacy significantly associate with each other to different extents. Only altruism and efficacy appear to be significant determinants of intent to use at $p<0.01$ and $p<0.05$, respectively. The scaled χ^2difference test shows that this model is not significantly different from Tsang's model.

Conclusion: Physician performance cannot be reliably evaluated and monitored when based purely on direct observations. The statistical results indicate that professional concerns associate with physicians' perceptions about the impacts of HIT and influence intent to use HIT. This paper shows a tendency of physicians to internalise factors that cannot be directly observed in the evaluation of HIT use. The study is advanced as of use in deriving policies that aim at coalescing evidence-based medical practice with humanism and thus as a significant contribution to the advancement of person-centered healthcare.

Keywords

Altruism, attitudes to computers, autonomy, decision-making/ethics, evidence-based medicine, humanism, information policy-making, knowledge use/utilization, person-centered healthcare, physician-patient relationship

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Accepted for publication: 22 August 2012

Introduction

The potential benefits of eHealth technologies in improving healthcare are frequently promoted by policy-makers and techno-enthusiasts [1]. The US and European experience suggests that health information technology (HIT) has not yet been sufficiently adopted for routine medical practice [2,3]. This situation suggests that applying HIT to healthcare may not be as beneficial as certain policymakers and techno-enthusiasts claim (see [1]). However, HIT implementations are underway globally [1]. It appears that the application of scientific evidence to clinical practice has extended to virtually every area of medicine [4], but not in eHealth policymaking. There is a pressing need for developing a measure of HIT use from a medical decision-making perspective.

In theory, one endeavour of medical informatics is to help in clinical reasoning (medical decision-making) based on a firm foundation of rationality [5]. Rationality, in economics, is referred to as 'a chosen action [not only] the best possible given the decision-maker's knowledge, but also that the knowledge employed be derived from coherent inferences' [6]. A desirable eHealth outcome is crucially reliant on being able to induce physicians faithfully to apply their knowledge during the use process. Based on a similar argument, Tsang [7] formulated a judicious HIT use measure. The model poses that professional concerns influence intent to use HIT [7]. The statistical results preliminarily support this theory [7]. It appears that the theory is worthy of further development.

Applying HIT for consultation implies adding extra procedure into the patient care process. A robust measure of HIT use cannot be detached from the contexts of medical practice [7]. Here, 'clinical reasoning' is of fundamental importance and encompasses the gamut of thinking about clinical medical practice' [5]. Knowledge, in the form of skilled care, is the basis and mediator of medical care [8]. The production of clinical knowledge is influenced by the physician-patient relationship [5]. The relationship involves agency, knowledge, trust and professionalism [8]. Medical decision-making is not simply something undertaken by a physician, perhaps aided by a computer [5] and neither can physician performance be reliably evaluated and monitored based on direct observations [9]. Certainly, 'the patient cannot check to see if the actions of [the] physician are as diligent as they could be' [9], due to the complexity of medical knowledge [8]. Also, the relationship between outcome and effort is to some extent random [9]. Ethical indoctrination has a crucial role in regulating physician behaviour [8,9]. It appears that eHealth success is more likely to be achieved through internalising professionalism into the process of HIT use. Tsang's [7] judicious HIT use model has been constructed in accordance with this line of thinking. However, the model does not address the cognitive aspect of medical decision-making.

The technology acceptance model (TAM) [10] suggests that user attitudes are affected by beliefs (perceived usefulness and ease of use) and are predictors of the behaviours of IT use (TAM is a dominant referent theoretical framework in IT acceptance [11]). Behavioural research suggests that choices are determined by attitudes and perceptions [12]. Note that physicians are expected to align their interests with the ill person and be free of any self-serving motivation [4]. Physicians' perceptions about the impacts of HIT on care benefits may crucially influence their HIT use decisions. This paper, therefore, focuses on developing a scale of perceived net (care) benefits. It will then be introduced into Tsang's [7] judicious HIT use model to form an alternative HIT use measure.

Methodology

Design

The data are a subset of survey data collected for developing a 7-dimensional eHealth success measure. Survey research is one of the most common methods for evaluating information system impacts [13]. A questionnaire is its primary data collection method [13]. A literature review of a sample of papers was conducted to collect the stylised facts. Table 1 summarises the stylised facts that define the perceived net benefits (*PNB*) constructs. The intent to use HIT for consultation (*Intent2Use*) and physician attributes (*PhyAttr*) constructs are adapted from Tsang [7]. A survey instrument was developed by: (1) combining the scales from some standard measures with established reliability and validity (see [14]) and (2) developing items based on the stylised facts of the relevant literature (see [15]). The second technique was used only when no appropriate measure could be identified [16]. Further details about the operationalisation are available on request.

The survey instrument was drafted in English and translated into Spanish. Appendix I presents the 37 7-point Likert items that operationalised the 3 constructs. A PubMed search was conducted to gather contact information of correspondence authors who published during 2007 to 2009 and worked in the public hospitals of Madrid and Andalusia. 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 authors who were likely to be physicians. For example, radiographers, pharmacists, *etc*., were filtered out.

Computer-Assisted Telephone Interviews were conducted during April 2010. The survey company contacted 866 physicians. The response rate was 25.29%, as 219 contacted physicians answered 1 or more questions. Discarding responses where only a few questions were answered is a recommended approach [22]. So, statistical analyses were performed on the 207 responses where the 37 items were completed.

Statistical analysis

The statistical analyses were performed by a freeware R version 2.15.0 [23] and largely by two packages: psych version 1.1.12 [24] and lavaan version 0.4-13 [25]. Imputation was performed by mice version 1.0 [26]

The analysis process included testing the data structure, imputation, dimension reduction and structural equation modelling.

First, the Mardia test result suggests that the multivariate normality assumption was violated (with p=0 for skew and kurtosis).

Second, the missing data rate is 2.56% (196 item nonresponses). It is within the 5% limit for applying listwise deletion [27]. However, applying listwise deletion implies discarding 46 unit responses. Predictive mean matching (PMM) imputation was applied to fill in the missing values once. The inferences of PMM tend to be robust to minor departures from the multivariate normality assumption [28].

Third, principal factor analysis was performed on each construct to reduce the data dimensions. Varimax rotation was also performed. Numbers of subfactors to exact were determined by parallel analyses (see [29]). Any item loaded insignificantly (with magnitude smaller than 0.40) or significantly on more than one subfactor was dropped iteratively [30]. A subfactor would be discarded if its explained variance was smaller than 0.10 [31], its eigenvalue was smaller than 1 [32] or it had only 1 significant indicator [29,33].

Fourth, the validated subfactors were submitted to perform Cronbach's [34] alpha (α) reliability tests. Items might be eliminated iteratively to obtain 0.60 α level – the minimum acceptable level for research in an exploratory mode [35]. Items with low corrected item-total correlations (<0.40) would also be eliminated [36].

Fifth, structural equation modelling (SEM) technique was then applied if the minimum indicator-response ratio

Table 1 Summary of the sample references†‡

Construct	Sample support references
Perceived Net Benefits	
Efficient healthcare and safer medicine	• The emphases of the European and US eHealth reforms [17,18]. • Improving accuracy of decisions in diagnosis, preventive care, disease management, drug dosing or drug prescribing [19] in timely manner.
Complementary use of explicit and tacit knowledge	• A system should facilitate bringing medical expert judgement and computer knowledgebase together [20].
Wider patient choices	• Decision-making can be defined as “the capacity to formulate alternatives, estimate effects and make choices” [21].

† The literature search was done based on the eHealth experience of European Union and the US. This summary is not meant to be an exhaustive literature review.
‡ See Table 1 in [7] for the summary of the physician attributes and intent to HIT for consultation constructs.

(1:5) for reliable estimations could be fulfilled [37]. For a sample of size equal to or greater than 200, Satorra-Bentler (SB) scaled statistics [38] appears to be a good general approach to adjust both the unreliable standard errors and fit indices due to non-normality [39]. An iterative process was applied to eliminate paths with insignificant *z* values at $p<0.05$ [32] or low multiple R^2 (<0.20) [40]. The model might be improved based on the modification indices if the SB χ^2 was significant at $p<0.05$. This approach is contested by some researchers, but often a necessary procedure [41]. This SEM process would also be performed to re-examine Tsang’s [7] model. Scaled χ^2 difference test would be performed to see whether the 2 models were significantly different or not.

Results

Physician characteristics

The gender ratio (M:F) is 54.6:39.6. Only 5.31% of the respondents were at a senior management level. The results are likely to reflect the opinions of HIT users (practicing physicians), rather than that of the senior management.

Approximately 84.5% of the respondents claimed using HIT frequently or for almost all consultations. The polyserial correlation tests show that frequency of HIT use positively and significantly associated with *itU*6 at $p<0.002$ and the other 6 *itU* items at least at $p<0.001$. Approximately 76.8% of the respondents indicated moderate to strong agreement to *itU*2, 51.7% to *itU*3, 68.6% to *itU*4, 86.5% to *itU*5 and 97.1% to *itU*6. That is, the vast majority of respondants showed willingness to use the Internet to search for information (*itU*6) and to use HIT to: (1) store and retrieve medical records (*itU*2), (2) collaborate with their colleagues (*itU*4) and (3) retrieve laboratory results (*itU*5). They appeared less ready to use HIT to assist clinical decision-making (*itU*3). In fact, the responses *itU3* and *itU4* suggest that they were least adaptive predisposition to technologies that aim at processing tacit knowledge.

Data reduction

The exploratory factor analyses recommended extracting 1 *Intent2Use* subfactor, 4 *PhyAttr* subfactors and 2 *PNB* subfactors. The Cronbach [34] reliability tests suggested that no item or subfactor might be eliminated. The α scores of the 7 subfactors ranged from 0.69 to 0.89 (Intent to use (*itU*), α=0.7; Altruism (*Altruism*), α=0.69; Autonomy (*Autonomy*), α=0.79; Physician-Patient Relationship (*Pat.Rel*), α=0.73; (Subconscious) Autonomy (*Sub.Auto*), α=0.69; Efficiency (*Efficiency*), α=0.89; Efficacy (*Efficacy*), α=0.78). The validated subfactors were submitted to perform SEMs.

Structural equation modelling

Model 1

Table 2 and Figure 1 illustrate the validated Model 1. No item was eliminated due to insignificant *z* value or low multiple R^2. Items *pa*13, *ben*7 and *pa*6 were eliminated iteratively to improve the model based on the modification indices (MIs) (*pa*13 ← *Pat.Rel*, MI=20.47; *pa*4 ↔ *ben*7, MI=19.51; *pa*6 ← *itU*, MI=16.33). Eliminating paths with large MIs was the chosen approach, as this makes the interpretability of the subfactors cleaner (interpretability is important for determining factor structure [29]). Model 1 demonstrated convergent validity, as all the *z* values were significant at least at $p<0.05$ [42]. Discriminant validity was also demonstrated, as no correlation estimate was greater than |1| after substracting (or adding) 1.96* standard error [43]. Thus, Model 1 fulfilled the minimum requirements to establish construct validity [32]. The 4 *PhyAttr* subfactors associated with each other significantly at least at $p<0.05$. The *PNB* subfactor *Efficiency* significantly associated with *Efficacy* and the 4 *PhyAttr* subfactors at least at $p<0.05$. *Efficacy* did not associated with *Pat.Rel* significantly (this path was eliminated). It associates with other subfactors significantly at $p<0.001$. Only *Altruism* and *Efficacy* proved to be significant determinants of *itU* at $p<0.01$ and $p<0.05$ respectively.

Table 2 Intent to use HIT, physician attributes and perceived net benefits

	χ^2†	d.f.	Pr(>χ^2)	RMSEA‡	SRMR	TLI	CFI
Fit statistics	183.077	155	0.061	0.03	0.05	0.976	0.978
ItU-PhyAttr-PNB (Model 1)							
	Estimate	**Std. error**		***z* value**	**Pr(>|*z*|)**	**95% CI**	
Path statistics							
pa9←Autonomy	0.823	0.051		16.114	0.000 ***	0.723	0.923
pa10←Autonomy	0.701	0.060		11.679	0.000 ***	0.583	0.818
pa11←Autonomy	0.712	0.064		11.203	0.000 ***	0.587	0.836
pa5←Pat.Rel	0.605	0.067		9.043	0.000 ***	0.474	0.737
pa8←Pat.Rel	0.838	0.056		15.037	0.000 ***	0.728	0.947
pa15←Pat.Rel	0.618	0.061		10.172	0.000 ***	0.499	0.737
pa12←Sub.Auto	0.725	0.066		11.038	0.000 ***	0.596	0.853
pa19←Sub.Auto	0.538	0.066		8.120	0.000 ***	0.408	0.667
pa1←Altruism	0.632	0.094		6.741	0.000 ***	0.448	0.816
pa2←Altruism	0.751	0.070		10.653	0.000 ***	0.613	0.889
pa4←Altruism	0.596	0.057		10.399	0.000 ***	0.484	0.708
ben1←Efficiency	0.780	0.051		15.184	0.000 ***	0.679	0.880
ben2←Efficiency	0.906	0.047		19.176	0.000 ***	0.813	0.998
ben3←Efficiency	0.866	0.058		14.860	0.000 ***	0.752	0.980
ben6←Efficacy	0.687	0.064		10.684	0.000 ***	0.561	0.813
ben8←Efficacy	0.736	0.063		11.748	0.000 ***	0.613	0.858
itU1←itU	0.578	0.062		9.256	0.000 ***	0.456	0.701
itU2←itU	0.538	0.059		9.136	0.000 ***	0.423	0.654
itU3←itU	0.415	0.050		8.233	0.000 ***	0.317	0.514
itU←Altruism	0.578	0.182		3.182	0.001 **	0.222	0.934
itU←Efficacy	0.364	0.175		2.075	0.038 *	0.020	0.707
Autonomy↔Pat.Rel	0.443	0.077		5.761	0.000 ***	0.292	0.594
Autonomy↔Sub.Auto	0.407	0.090		4.527	0.000 ***	0.231	0.583
Autonomy↔Altruism	0.253	0.077		3.284	0.001 **	0.102	0.404
Autonomy↔Efficiency	0.166	0.079		2.096	0.036 *	0.011	0.321
Autonomy↔Efficacy	0.303	0.079		3.856	0.000 ***	0.149	0.457
Pat.Rel↔Sub.Auto	0.406	0.078		5.199	0.000 ***	0.253	0.560
Pat.Rel↔Altruism	0.187	0.080		2.332	0.020 *	0.030	0.344
Pat.Rel↔Efficiency	-0.292	0.060		-4.885	0.000 ***	-0.409	-0.175
Sub.Auto↔Altruism	0.564	0.090		6.289	0.000 ***	0.388	0.740
Sub.Auto↔Efficiency	0.487	0.080		6.099	0.000 ***	0.330	0.643
Sub.Auto↔Efficacy	0.658	0.084		7.828	0.000 ***	0.493	0.822
Altruism↔Efficiency	0.469	0.068		6.885	0.000 ***	0.336	0.603
Altruism↔Efficacy	0.657	0.081		8.069	0.000 ***	0.497	0.816
Efficiency↔Efficacy	0.763	0.059		12.975	0.000 ***	0.648	0.879

* indicates significance at $p<0.05$, ** at $p<0.01$ and *** at $p<0.001$.
† Satorra-Bentler scaling correction factor: 1.066
‡RMSEA Index 90% CI: (0, 0.045)
d.f., degrees of freedom; RMSEA, root mean square error of approximation; SRMR, standardised root mean residual; TLI, Tucker-Lewis index; CFI, comparative fit index.

Figure 1 **Path diagram – Physician attributes, perceived net benefits and intent to use HIT (**Model 1)

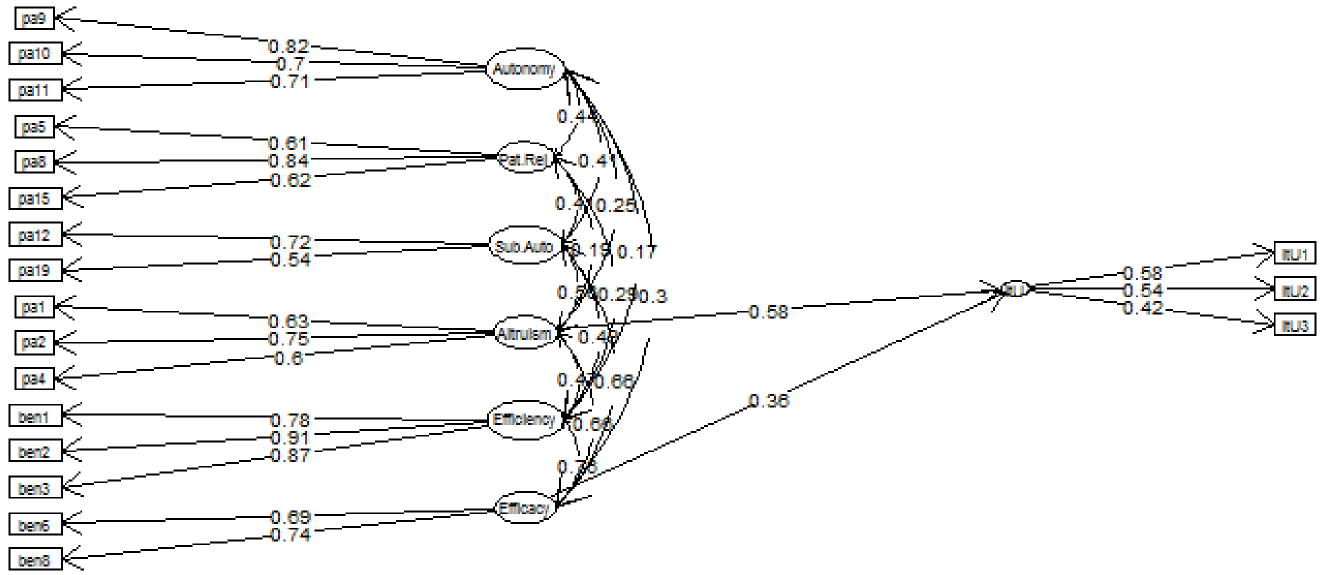

Figure 2 **Path Diagram – Intent to use HIT and physician attributes (**Model 2)

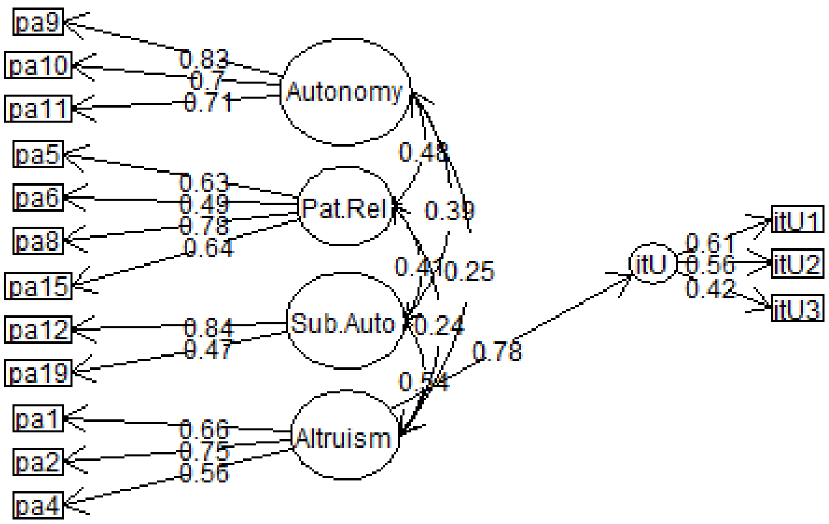

Table 3 Scaled χ^2 difference test

	AIC	χ^2†	d.f.	$\Delta\chi^2$	Δd.f.	Pr(>χ^2)
ItU-PhyAttr (model 2)	8104.26	120.23	98			
ItU-PhyAttr-PNB (model 1)	9880.09	183.08	155	62.95	57	0.2739

d.f., degrees of freedom; AIC, Akaike information criterion.
† Satorra-Bentler scaling correction factors are 1.056 for the ItU-PhyAttr model and 1.066 for ItU-PhyAttr-PNB model.

Table 2 also reports the fit indices. SB χ^2 was insignificant at $p<0.05$. Thus, Model 1 may not be rejected. Scaling correction factor (SCF) is 1.066 suggesting that the maximum likelihood (ML) χ^2 is overstated approximately by 6.6%. lavaan does not report AGFI (adjusted goodness-of-fit index) and GFI (goodness-of-fit index) (recent studies suggest that AGFI and GFI may not be applied to assess model fit [40]). However, it provides sufficient indices for making judgements based on double fit criteria [44]. CFI (comparative fit index) and TLI (Tucker-Lewis index) surpass the 0.90 recommended threshold for a good fit [29]. RMSEA (root mean square error of approximation) smaller than 0.05 may indicate 'very good' fit [45]. SRMR (standardised root mean residual) is smaller than 0.08 (the recommended threshold) [44]. All the double fit criteria are fulfilled [44]. It appears that the data fit Model 1 extremely well.

Model 2 (with a comparison with Model 1)

SB χ^2 was initially shown to be significant at $p<0.05$. However, it became insignificant ($p=0.063$) after eliminating *pa*13 (*pa*13 ← *Pat.Rel* with MI=17.651). The path statistics of the validated Model 2 are depicted in Figure 2 (detailed statistics are available on request). The results suggest that the 4 *PhyAttr* subfactors associate with each other significantly at least at $p<0.01$, perhaps mostly at $p<0.001$. *Altruism* is the sole significant determinant of *itU* (with $p<0.001$). These paths appear to be more significant than those in Model 1. The data also seem to fit this model extremely well (CFI=0.97; TLI=0.967; RMSEA=0.033; SRMR=0.06). The scaled χ^2 difference test shows that Model 2 is not significantly different from Model 1 (see Table 3).

Discussion

This paper introduces perceptions about the impacts of HIT on care benefits (Model 1) into Tsang's [7] judicious HIT use model (Model 2). Statistical analyses were performed on a subset of survey data. The 4 physician attributes (*PhyAttr*) and the 2 perceived net benefits (*PNB*) subfactors are shown to be associated with each other at least at $p<0.05$ (except *Efficacy* does not seem to associate with *Pat.Rel*). Only *Altruism* and *Efficacy* show to be significant determinants of *itU* at $p<0.01$ and $p<0.05$ respectively. Altruism is not only evidenced by *Altruism* being a significant determinant of *itU*, but also physicians' concerns about efficiency and efficacy of medical care.

The result of the scaled χ^2 difference test shows that Model 1 is not significantly different from Model 2. However, if deriving a parsimonious model is a goal, then Model 2 seems to be a better choice, as its AIC (Akaike Information Criterion) is smaller [40]. Note that a model with more d.f.'s (degrees of freedom) generally offers more dimensions to disconfirm it [33]. Model 1 appears to be the preferred model. This aspect may be examined in further research.

Ethics is an important, but yet not a mainstream IS research area [46]. Professionalism has been considered to be crucial to implementing desirable care outcomes [8,9,47]. Developing a quantifiable theory of judicious HIT use for consultation is certainly an important topic. However, a PubMed search suggests that Tsang's work [7] is probably the first attempt. So, the statistical results can only be compared with that of Tsang's work [7]. The results also seem to be consistent with theories originated from different disciplines. The model shows to be reliable. It therefore appears worthy of further development.

In future research, technological factors may be introduced into the discussion. The approach may be applied to modelling other medical decisions. Further tests may be conducted to examine the application of the perceived net benefits scale to exacting physicians' attitudes towards other decision problems.

Conclusion

Medicine has been a science-using and compassionate practice [4,48-50]. Literally, physician performance may only be reliably evaluated from a sociotechnical perspective. This paper applies this principle to model a specific medical decision problem – HIT use. It proposes introducing a scale of perceptions about the impacts of HIT on care benefits into a model of judicious HIT use [7]. The statistical results suggest that professional concerns and perceptions influence intent to use HIT directly or indirectly to different extents. This implies that quantity of HIT use is not a comprehensive measure of HIT use.

The statistical results support the idea that physician performance cannot be reliably evaluated and monitored purely based on direct observations [9]. Perhaps, more research efforts may be put forth into developing schemes that remunerate physicians based on intrinsic-extrinsic incentives (see [51,52], for example). This research direction may contribute to policymaking for coalescing evidence-based medical practice with humanism to care for patients as whole persons as part of the development of person-centered medicine [4,48-50]. It may also contribute to building a trusting relationship between healthcare managers and physicians through a better understanding of medical practice.

Acknowledgements and Conflicts of Interest

The Computer Assisted Telephone Interviews cost was funded by the University of Granada. ST declares that Professor Luis Molina Fernández also had full access to the survey data. ST acknowledges his contributions to funding acquisition, coordinating with the survey company and translating the survey instrument. ST appreciates his and Professor Daniel Arias Aranda's serving as scientific advisors for a related project. ST also acknowledges Dr. Michael Loughlin of Manchester Metropolitan University, UK for some fruitful discussions and Professor Yves Rosseel, a contributor of lavaan, for discussions of some SEM techniques. No personal medical information was employed. The potential candidates were identified from a bibliographic database. The physicians were not reimbursed for their voluntary participation in the interviews. The author declares no conflicts of interest.

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Appendix 1 The 37 survey items†‡

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 Perceived Net Benefits/Usefulness

ben1 The system enables me to accomplish tasks faster.
ben2 The system enables me to be more productive.
ben3 The system makes it easier to do my job.
ben4 The system improves quality of clinical decisions.
ben5 The system improves quality of communication with patients.
ben6 The system helps avoiding medication errors.
ben7 The system empowers patient choice as it enhances my awareness of alternative care, e.g., diagnoses, medications, therapies, *etc*.
ben8 The system improves delivery of care that meets guidelines.
ben9 The system helps timely access to patient records.
ben10 Overall, the system enhances my effectiveness.
ben11 Overall, I find the system useful in my job.

† The 26 items that operationalise the intent to use and physician attributes constructs have been published in Tsang [7]. 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).