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Modeling the acceptance of clinical information systems among hospital medical staff: An extended TAM model

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ABSTRACT

Recent empirical research has utilized the Technology Acceptance Model (TAM) to advance the understanding of doctors' and nurses' technology acceptance in the workplace. However, the majority of the reported studies are either qualitative in nature or use small convenience samples of medical staff. Additionally, in very few studies moderators are either used or assessed despite their importance in TAM based research. The present study focuses on the application of TAM in order to explain the intention to use clinical information systems, in a random sample of 604 medical staff (534 physicians) working in 14 hospitals in Greece. We introduce physicians' specialty as a moderator in TAM and test medical staff's information and communication technology (ICT) knowledge and ICT feature demands, as external variables. The results show that TAM predicts a substantial proportion of the intention to use clinical information systems. Findings make a contribution to the literature by replicating, explaining and advancing the TAM, whereas theory is benefited by the addition of external variables and medical specialty as a moderator. Recommendations for further research are discussed.

1. Introduction

During the last 20 years, several theoretical models have been proposed to assess and explain end – users' acceptance behavior towards information and communication technology (ICT for short). The Technology Acceptance Model (TAM) [1] which is applied and empirically tested over a wide spectrum of applications of ICT, is one of the most well recognized theoretical modes among them [2,3]. Recent studies provide evidence that TAM is a good predictor of behavioral intent to accept technology in the health sector [4–6].

In TAM, technology acceptance and use is determined by behavioral intention (BI). BI in turn, is affected by attitude towards use (ATT), as well as the direct and indirect effects of perceived ease of use (PEoU) and perceived usefulness (PU). Both PEoU and PU jointly affect ATT, whilst PEoU has a direct impact on PU [4,6,7] (see also Fig. 1 for a graphical sketch of direct and indirect relationships of the TAM). The TAM model is an analytical simplification of how functionality and interface characteristics relate to adoption decisions; understanding why clinicians hold certain beliefs about CIS is valuable because beliefs influence subsequent behavior and they are amenable to manipulations through appropriate interventions [8].

Although TAM is considered as a well-recognized model in the field of information systems, little systematic research has been conducted in the health care context indicating a significant gap in knowledge. Therefore, there is a strong current need to develop and gain empirical support for the TAM within health organizations; more replication studies are needed so that confidence is gained in whether TAM is a good fitting theory in health care. This may be achieved by using larger size samples, by investigating and exploring new theoretically motivated variables and relationships, by testing external variables, as well as by applying TAM on different profession-specific groups of personnel (e.g. different physician specialties) etc.

Yarbrough and Smith [4] and Holden and Karsh [6], in their meta-analytic reviews concerning the application of TAM in health care, reported significant heterogeneity among the studies in terms of sample characteristics and technologies studied. Furthermore, several inconsistencies were found concerning the relationships among TAM variables. Specifically, both reviews have demonstrated that the majority of existing TAM studies in health care: (1) have used small convenience samples of medical staff, (2) have

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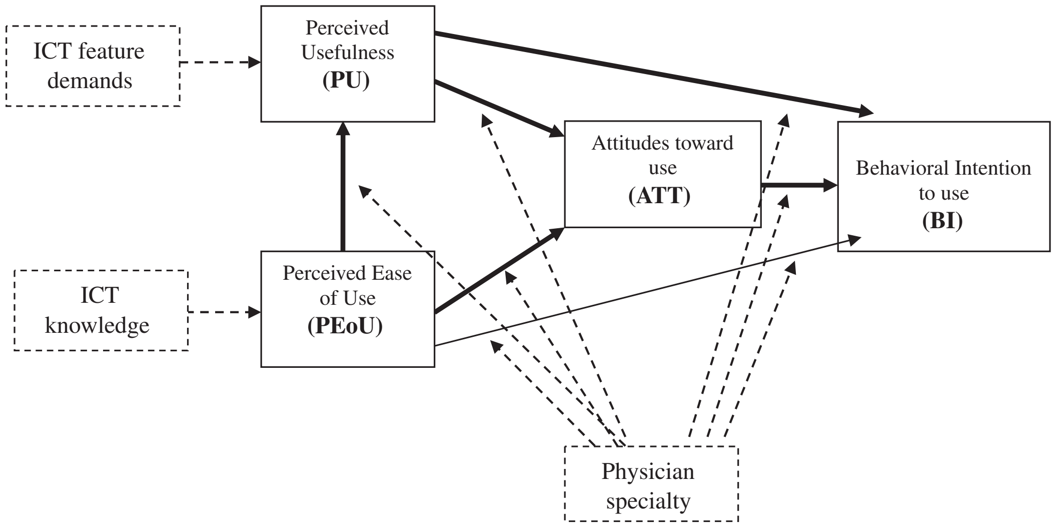

Fig. 1. Representation of the TAM model and the proposed extended TAM model. Bold lines represent the classical TAM Model. Normal lines represent paths tested in previous studies. Dot lines, represent constructs and paths tested for first time in Technology Acceptance Models. "Physician Specialty" represents profession-specific differences that moderate the relationships between TAM variables.

not used moderator variables, (i.e., variables that alter the direction or strength of the relation between a predictor and an outcome), (3) have not used external variables (i.e., variables outside TAM that reveal how perceptions of PU and PEoU are formed), (4) have not tested a uniform and specific model of relationships between TAM variables and (5) have used generic non-contextualized measures (i.e. the items measuring the TAM variables were generic and not health care specific).

The primary aim of this research is:

1. To test the applicability and effectiveness of TAM in health care sector using a large sample of health-care personnel including mostly medical doctors, drawn from different specialty categories and nursing staff.
2. To examine the way ICT knowledge and ICT feature demands as well specialty differences affect the intention of medical staff to use clinical information systems (CIS for short) in every day practice.

In order to achieve both goals an extended TAM is developed and tested, using the structural equation modeling (SEM for short) approach as well as data obtained from a random sample of 604 clinicians (534 physicians) working in 14 hospitals in Greece.

In the present study, we consider a general approach towards CIS's which are defined as the application of both computer hardware and software for information processing dealing with the storage, retrieval, sharing, and use of health care information, data, and knowledge for both communication and decision-making [6]. Consecutively we do not test a specific CIS but instead we are interested in studying the factors which influence and shape clinicians' intentions to use CIS.

Such an approach helps to better understand what makes clinicians ignore these systems and explains medical professionals' attitude towards ICT adoption and use. By extension, it raises implications for the hospital administrators, as they should apply appropriate policies in order to encourage the frequent and efficient use of ICT.

In the same vein we used self-reported (ICT) knowledge and ICT feature demands as external variables in TAM [9]. ICT knowledge is defined as "how much" clinicians perceived to know about ICT, and ICT feature demands refers to "how sophisticated" CIS must be before clinicians would be willing to use them.

Over the sections which follow we briefly overview TAM clinical context applications, present the salient aspects of the methodology, show and discuss results and summarize key findings.

2. Literature review: TAM in clinical context

A recent review concerning TAM in the health sector [6] identified 16 distinct datasets analyzed in 21 studies of clinicians using CIS for patient care. However, the researchers did not perform a quantitative analysis, due to the significant heterogeneity with respect to sample characteristics, specific technologies studied, and technology function.

Of the 16 data sets analyzed, 11 used TAM whereas 5 used TAM related models, such as TAM2 [10] or the Unified Theory of Acceptance and Use of Technology (UTAUT) [11]. TAM2 is an update of TAM, in which the component ATT (which originally mediated some of the influence of PU and PEoU) is removed from the model while a new variable subject norm (SN) is added, in order to capture the social influence (i.e. from colleagues or bosses) that compels the users to use ICT. UTAUT incorporates PU into a performance expectancy construct, PEoU into effort expectancy, and SN into social influence. UTAUT aims to explain user behavioral intentions to use an IS and subsequent usage behavior.

Of the 11 data sets analyzed using TAM, 7 contained data from physician samples. The specialties covered were related to endoscopy, disability care, general practice, nursing, and medical technicians (Table 1).

The 11 data sets mentioned in Table 1 suggest that TAM consistently predicts a good portion of variation in clinician intention to accept new technology, with the reported percentage of variance explained in the dependent variable (e.g., R^2) being reasonably high, ranging from 40% to 70%. Although these data sets provide evidence that the TAM constructs generally hold in a clinical context, great variability was found in the operational implementation of the constructs used within and between studies, despite the fact that TAM constructs were similarly defined and the questionnaires used were well established and validated [6].

As an example, TAM was tested among a sample of acute care physicians in a Hong Kong hospital to determine physicians' acceptance of telemedicine [12]. Results provide support for the adequate fit of the TAM. Moreover, the relationship between PU and

Table 1
Summary of reviewed data sets of TAM in health care [5].

Population studied	Sample (N)	Country setting
Endoscopy involved staff	10	UK
Disability care providers	141	USA
General practitioners and specialists	91	Australia
General practitioners and specialists	242	Finland
General practitioners and specialists	408	Hong Kong
Nurses	61	Australia
Physio-therapists	49	UK
Nurses	252	Taiwan
Pharmacists, physicians, nurses, managers, and others	173	USA
Senior health care trainees, physician assistants, and other technology staff at hospitals and clinics	77	USA
Physicians, nurses and medical technicians	123	Taiwan

both ATT and BI seemed to be significant. However, no support was found as far as the relationship between PEoU and either PU or ATT is concerned. The researchers raised the argument that the PEoU component of the TAM may not be applicable for individuals with above-average intelligence. However, Paré et al. [8] reported a statistical significant result for the relationship between PEoU and ATT. It is plausible that when respondents have hands-on experience with using a CIS system, then the relationship between PEoU and ATT and BI may be statistically significant. Therefore evidence is probably not strong enough to justify the exclusion of the PEoU construct from TAM.

Moreover, less attention has been given to the inclusion of external variables that are unique to clinician population and explain formation of beliefs in TAM [4]. It was proposed in the literature [1] that external variables of a TAM can affect beliefs of PEoU and PU. In the application of TAM in health care several external variables were added such as, perceived system characteristics (i.e. how well the system performs [13,14] and how relevant the system is to one's job [15]), as well as personal characteristics of users [15,16] and psychological variables, such as ownership [8] and trust [17].

3. Overview of research aims and hypotheses

The objective of this study is twofold: (1) To replicate the TAM model and (2) to extend the TAM model in the health sector. In order to replicate the TAM, the basic items of the TAM constructs (i.e. PU, PEoU, ATT and BI) are measured using the largest sample size ever tested with TAM in the health sector, (604 clinicians) including physicians (534) from specialties that have never been tested before (e.g. surgeons, pathologists), using structural equation modeling (SEM). In order to extend the TAM model, we use two external variables that are unique to the clinician population, namely clinicians' ICT knowledge and ICT feature demands in clinical settings (see Fig. 1). Specifically, drawing from other research in ICT and medical care [9], we will test the influence of clinicians' computer knowledge (i.e. how much medical staff know about computers) on PEoU and clinicians computer feature demand (i.e. medical staffs' preferences of the capabilities of medical computing systems) on PU.

Although in the literature concerning TAM in the health sector there were studies that utilized data from a mix of physicians, nurses, pharmacists, and medical technicians [15,18], none of these studies examined profession-specific differences (e.g. among different physician specialties), possibly due to small sample sizes. It is plausible that physicians' specialty may act as moderator influencing the strength of the relationship between criterion and predictor variables in the TAM model. Prior research suggests that subject type may influence the strength of relationships of the variables in the TAM model [3].

4. Research method

The study aimed first to determine whether, and to what extent, BI is associated with ATT, PU and PEoU in clinical settings. Towards these aims we followed specific steps:

First, TAM constructs (i.e., PU, PEoU, ATT and BI) are measured. Based on recent research [4,6], we expect positive correlations between the aforementioned constructs.

Second, we aimed to test whether, and to what extent, ATT mediate PU and PEoU effects on BI using SEM (see Fig. 1). We expected that ATT would at least partially mediate PU and PEoU effects on BI.

Third, using SEM we tested whether clinicians' ICT knowledge influence PEoU and whether clinicians' and ICT feature demands influence PU (Fig. 1). We expect knowledge to positively influence PEoU and feature demands to negatively influence PU [3].

Fourth, we used multi-group analysis of structural invariance (MASI for short) to test for differences in structural weights of PU, PEoU and ATT in BI across different physician specialties (surgery and pathology) [19,20].

For our analyses we used modern quantitative methods: confirmatory factor analysis (CFA for short), SEM and MASI. These methods are based on latent variable modeling, where the measurement error is minimized through the use of multiple indicators of latent variables prior to testing model fit. The estimation method employed was maximum likelihood (ML) for normal data and the variance adjusted weighted least squares estimator (WLSMV), for categorical data. Specifically, CFA was used to test our measurement model's (i.e. the relationships between latent factors and measurement variables) convergent and discriminant validity and the presence of common method bias in our data (Section 4.3). SEM was used to test the causal-effect relations among latent constructs. The bootstrapping procedure was used in order to correct for standard errors (Section 4.3). Finally MASI was used to test specific differences between different physician specialties. Based on the methodology literature a critical issue in moderation analysis is the sample size of the groups compared; unequal sample sizes across groups decrease power [21]. In our case our data permit us to test differences between pathologists ($n = 233$) and surgeons ($n = 215$) due to adequate sample sizes we obtained for these specialties.

When latent (invisible) variables are involved, MASI provides more rigorous test of differences in structural weights across groups than analysis of covariance. The test can answer the question: do PU, PEoU and ATT have equivalent structural weights predicting BI across ICT use for surgeons and pathologists? Such comparisons, in order to be meaningful, would necessitate evidence of measurement invariance between responses obtained from the different groups. Invariance reveals the extent to which responses maintain their meaning across groups [22,23]. Five models explained in Section 4.4 and suggested in relevant theory are tested in hierarchical sequence. Due to a lack of literature examining the role of physicians' medical specialty involving the TAM, we had no a priori reasons to suspect that variations in medical specialty may influence the clinicians' frame of reference and, thereby, the meaning or scaling of the TAM constructs.

4.1. Sampling method and participants

A preliminary questionnaire was designed and sent out for review to five experts who had practical and academic experience with computer systems in health care. This phase was used to clarify the wording, content, and general layout of the survey instrument.

The main survey was carried out via personal interviews, involving 1015 individuals (doctors and nurses) who where ICT users, from 13 main state hospitals and one private hospital located across different regions of Greece. Individuals were identified by the human resources department of each hospital. Specifically, complete lists of all individuals who use medical informatics were given to the researchers. Data collection process took place from July to December 2008. The questionnaire was given to all individuals and appointments for interviews were arranged. This research focuses on the actual users, including (in the sample) members of the medical and nursing personnel who use and interact with computers on a daily basis. No monetary incentive was provided to respondents.

Out of a total population of 1015 contacted users, 604 answered the questionnaire (response rate of 59.5%). Doctors and nurses were given the following explanation for the purposes of the study: "*This is an effort to combine research into factors affecting CIS use, in clinical settings. A CIS is defined as the application of both computer hardware and software for information processing dealing with the storage, retrieval, sharing, and use of health care information, data, and knowledge for both communication and decision-making. Your participation is not obligatory; you will answer a questionnaire without filling in anything that will identify you, or your department. The results will be used so that the factors that influence CIS use in healthcare are better understood*". In an effort to assess the possible impact of response bias, we contacted 40 randomly selected non-respondents directly on the telephone and requested input. Twenty of them complied with the request. Comparison of respondents and non-respondents indicated that they did not differ with respect to any of the variables of interest in the present study.

The sample consisted of 60.3% males with mean age 36.45 years (SD = 7.9 years). Average tenure in years was five (SD = 6.2 years). The percentage of medical personnel was 88.4%. The distribution of the main physician specialties was 35.6% surgery, 38.6% pathology, 7.5% laboratory specialties and 6.8% general medicine. Physicians reported a mean of 12.52 (SD = 10.8) hours of hands-on use of a computer per week. Nursing personnel reported a mean of 7.04 (SD = 9.9) hours of hands-on use of a computer per week. Average hours of hand-on use of computer per week was 11.9 (SD = 10.8) for the total sample.

4.2. Measurement of constructs

All constructs included in the analysis were based on multi-item scales the psychometric properties of which are well established. As participants were Greek-speaking, all the scales used were first translated into Greek by two translators, who compared their versions until agreeing on the most correct translation, and then back-translated into English by a bilingual, native English speaking translator, following the procedure recommended in the literature [24]. No significant discrepancies between the original English version and the back-translated version were found. The specific measures used in the analysis, along with sample items of the relevant constructs, are outlined.

4.3. TAM variables

In this study, responses to the items of TAM constructs (i.e., PU, PEoU, ATT and BI) were measured on a 5-point Likert scale from 1 = strongly disagree, to 5 = strongly agree (see Table 2).

4.4. Perceived usefulness of clinical information systems (PU)

We used 6 items from the work of Davis [1] original TAM. Cronbach's reliability coefficient for PU was 0.92. The overall PU score for each respondent was obtained by averaging the scores across the six items.

4.5. Perceived ease of use of clinical information systems (PEoU)

We used 6 items from the work of Davis [4] original. Cronbach's reliability coefficient for PEoU was 0.93. The overall PEoU score for each respondent was obtained by averaging the scores across the six items.

Table 2
Technology Acceptance Model (TAM) variables: results of confirmatory factor analysis for the total sample (N = 604) of clinicians.

Items	Standardized factor loadings					
	PEoU	PU	ATT	BI	SMC	AVE
PEoU1 – Learning to operate CIS would be easy for me	0.85	–	–	–	0.72	
PEoU2 – I would find it easy to get CIS to do what I want it to do	0.87	–	–	–	0.75	
PEoU3 – My interaction with CIS would be clear and understandable	0.87	–	–	–	0.75	
PEoU4 – I would find CIS to be flexible to interact	0.67	–	–	–	0.45	
PEoU5 – It would be easy for me to become skillful at using CIS	0.85	–	–	–	0.72	
PEoU6 – I would find CIS easy to use	0.84	–	–	–	0.71	
						0.56
PU1 – Using CIS in my job would enable me to accomplish tasks more quickly	–	0.80	–	–	0.64	
PU2 – Using CIS would improve my job performance	–	0.91	–	–	0.83	
PU3 – Using CIS in my job would increase my productivity	–	0.93	–	–	0.86	
PU4 – Using CIS would enhance my effectiveness on the job	–	0.85	–	–	0.73	
PU5 – Using CIS would make it easier to do my job	–	0.78	–	–	0.61	
PU6 – I would find CIS useful in my job	–	0.63	–	–	0.40	
						0.60
ATT1 – Using CIS is advisable in clinical practice	–	–	0.69	–	0.48	
ATT2 – Using CIS is a pleasant idea	–	–	0.93	–	0.86	
ATT3 – I will enjoy using CIS	–	–	0.86	–	0.75	
ATT4 – I will be satisfied in using CIS	–	–	0.91	–	0.83	
						0.56
BI1 – I predict that I will use CIS on a regular basis in the future	–	–		0.60	0.36	
BI2 – CIS will be one of my favorite technologies for my work	–	–	–	0.78	0.61	
BI3 – I intent to use CIS in my work				0.80	0.64	
	–	–	–			0.55

Note: 1–5 scale: 1 = strongly disagree, 2 = disagree, 3 = neutral, 4 = agree, 5 = strongly agree). CIS: clinical information systems; SMC: squared multiple correlations; AVE: average variance extracted.

4.6. Attitudes towards use (ATT)

We used six items from the work of Davis et al. [7]. Cronbach's reliability coefficient PU was 0.91. The overall ATT score for each respondent was obtained by averaging the scores across the six items.

4.7. Behavioral intention (BI)

We used three items from the work of Davis [1] original TAM. Cronbach's reliability coefficient for PEoU was 0.77. The overall BI score for each respondent was obtained by averaging the scores across the three items.

4.8. ICT knowledge

We adopted 15 items of the computer knowledge scale developed by Cork et al. [9] to assess the computer knowledge attribute (see Appendix A). For each item, using a three-point response scale, (*1-I don't understand the distinction at all, 2-I have a general appreciation of the distinction but could not define it, 3-I can define the distinction precisely*) respondents indicated the extent of their understanding of the distinction between a pair of computing concepts. Exploratory factor analysis of the 15 items using the Mplus (version 5.21) software [25] and the WLSMV estimator [26] resulted in the extraction of one factor. Cronbach's reliability coefficient for all 15 items was 0.93. The overall ICT knowledge factor score for each respondent was obtained by averaging the scores across the specific items.

4.9. ICT feature demands

We used 15 items of the computer feature demands scale developed by Cork et al. [9] to assess the computer feature demand attribute (see Appendix B). Each item represents a feature or capability of a CIS. In the sequel each item is assessed over a discrete ordered four points scale in which a "1" valuation corresponds to "vital" requirement and "4" maps a "not necessary" assessment. Exploratory factor analysis of the 15 items comprising the *Computer feature demands scale*, using the Mplus (version 5.21) software [28] and the WLSMV estimator [26], resulted in the extraction of two meaningful factors. The first factor refers to demand for sophisticated computer features. The second factor refers to demand for computer usability (DCU). Cronbach's reliability coefficient for sophisticated computer features (SCF) was 0.80 and for the demand for computer usability was 0.82. For all 15 items Cronbach reliability was 0.88. The overall computer feature demands factor score for each respondent was obtained by averaging the scores across the 15 items.

4.10. Statistical method considerations-analytical strategy

Prior analysis data screening was performed and data were tested for deviation from normality [27]. Analysis of Moment Structures (AMOS software, version 7.0) [28] was used for the MASI equivalence.

Following recommendations set forth by Anderson and Gerbing [29], we tested the TAM model using a two-stage analytic procedure. Specifically, a structural equation model is composed of a measurement model and a structural model. In the first step of analyses step, we fitted a measurement model to the data and in the second step we tested the underlying structural model. During the first step, a measurement model was assessed, which allowed the underlying latent constructs to correlate freely and constrained each item to load only to the factor for which it was a proposed indicator. To further assess discriminant validity of the TAM constructs, we compared the measurement model with a model that constrained the correlations among the constructs to be equal and examined the change in chi-square (χ^2). A non-significant χ^2 value indicates acceptance of the more parsimonious of the nested models. Evidence that common method variance does not account for the observed relationships would be provided if a four factor model, representing each variable as a separate construct, is superior to a one-factor model.

We followed procedures used in literature [30] to evaluate convergent validity. Convergent validity is established if the average variance extracted (AVE) for each factor accounts for 0.50 or more of the total variance and is demonstrated by statistically significant path coefficients. Calculated values of AVE for each one of the four PEoU, PU, ATT and BI items was found greater than 0.50, thus convergent validity was established for our model (see Table 2).

Because the χ^2 statistic is highly sensitive to sample size, we employed several statistics to assess model fitness [31]: (a) Root Mean Square Error Approximation (RMSEA): 0 = an exact fit,<0.05 = a close fit, 0.05–0.08 = a fair fit, 0.08–0.10 = a mediocre fit, and > 0.10 = a poor fit (AMOS also computes a 90% confidence interval around RMSEA); (b) Comparative Fit Index (CFI): best if above 0.9; (c) Tucker – Lewis Index (TLI): best if above 0.9; (d) Akaike Information Criterion (AIC); (e) Root Mean Square Residual (RMR) best fits for values less than 0.10. For model comparisons, smaller values in AIC represent a better fit of the model.

In order to select among the TAM competing structural models specifying total effects (direct and indirect), complete mediation and partial mediation, we applied model selection for structural

Table 3
Descriptive statistics and inter-correlations for the total sample ($N = 604$).

	M	SD	1	2	3	4	5	6	7	8	9	10	11
1. Gender[a]	1.40	0.49	–										
2. Age	36.4	7.88	−0.18**	–									
3. Tenure	5.04	6.19	0.00	0.76**	–								
4. Specialty [b]	1.62	1.01	−0.07	−0.10**	−0.24**	–							
5. Hours using PC/week	11.9	10.8	−0.17**	−0.05	−0.09*	0.14**	–						
6. ICT knowledge	2.26	0.55	−0.20**	−0.14**	−0.24**	0.03	0.29**	(0.93)					
7. ICT feature demands	1.98	0.33	0.06	−0.12**	−0.11**	0.06	0.02	−0.02	(0.88)				
8. PEoU of CIS	3.49	0.65	−0.12**	−0.05	−0.14**	0.17**	0.31**	0.47**	−0.03	(0.93)			
9. PU of CIS	4.09	0.60	−0.09*	0.05	0.02	0.05	0.15**	0.22**	−0.48**	0.51**	(0.92)		
10. ATT towards use CIS	3.90	0.63	−0.09*	0.07	0.05	0.05	0.20**	0.24**	−0.36**	0.56**	0.79**	(0.91)	
11. BI	3.72	0.55	−0.11**	0.04	−0.07	0.11**	0.24**	0.30**	−0.19**	0.63**	0.68**	0.74**	(0.77)

Reliabilities are in parentheses.
[a] Gender is coded: 1 = male 2 = female;
[b] Specialty: 0 = nurse; 1 = surgeons; 2 = pathologists; 4 = laboratory specialties; 5 = general practitioners.
* $p < 0.05$ (two tailed).
** $p < 0.01$ (two tailed).

equation models [28,32]. Specifically, AMOS 7.0 permits specification searches for the best theoretical model given an initial model using Akaike Information Criterion (AIC). AIC, represents an information theoretic approach to model selection; smaller AIC values indicate better fit. AIC is assessed from the data for each fitted model and it is possible to be used for the computation of model weights in order to quantify the uncertainty that each model is the best model [33]. Specifically, one can search through the vast set of possible models for the best ones and compare individual nested models through the employment of heuristic specification research strategies. In the present research, we employed a stepwise strategy in model selection, which included both forward selection and backward elimination features. Furthermore, under this framework, it is meaningful to speak of the probability of a model. Raw AIC values can be easily transformed to the so-called Akaike weights, which can be directly interpreted as conditional probabilities for each model [34].

In addition, we used bootstrapping procedures to test significance of mediation [35]. Bootstrapping is a nonparametric approach to hypothesis testing whereby one estimates the standard errors empirically using the available data. Operationally, in bootstrapping, multiple samples are drawn, with replacement, from the original data set, and the model is re-estimated on each sample, which results in a number of path estimates that is equal to the number of samples drawn from the original data set. Following current recommendations, we re-sampled 1000 times and used the percentile method to create 95% confidence intervals [35].

In order to avoid problems associated with common method variance often found in cross sectional survey research, several steps described in the literature [36] were taken. First, all participants were informed that their participation was completely voluntary and confidential. Second, items referring to the same construct were positioned in different locations throughout the questionnaire and several items were reverse phrased. Third, we adopted Harman's one-factor test (see Table 4).

4.11. Invariance analysis method

To examine whether medical specialty has an effect on the model with the best fit to the data, we followed the sequence of MASI [19,20]. Tests of factorial invariance across multiple groups involve a hierarchical ordering of nested models. Any two models are nested, as long as the set of parameters estimated in the more restrictive model is a subset of the parameters in the less restrictive model. When a model is a subset of a larger model, the difference between them can be tested by subtracting the two chi-square values and testing this value against the critical value associated with the difference in degrees of freedom. According to relative theory, chi-square test is very powerful and, where the hypothesis of equal factor loadings or structural weights is not rejected, it provides strong support that observed differences across subgroups in parameters may be expressed by chance [19]. Factor loadings and model-data fit were assessed for each group (pathologists and surgeons). Low item-factor loadings indicate that the factors did not have the same meaning in the subgroup, thus comparison is meaningless and subgroup should be rejected, whereas factor loadings grater than 0.60 are acceptable. The following five models were tested in a hierarchical sequence:

Model 1 (configural invariance model) represents the totally non-invariant model with no between-group equality constraints on any of the model parameters. This is the least restrictive model, but it has great importance as, if the model cannot fit the data, none of the more restrictive models will do so.

In *Model 2* (the metric invariance model), equality constraints were imposed on the factor loadings across the groups. This model reveals whether the constructs are manifested differently between groups and it is a prerequisite for meaningful cross-group comparisons [19]. Group comparisons can still be performed even in the case of few non-invariant items because few items will not heavily influence such comparisons (partial metric invariance, [22]).

Model 3 (the measurement error invariance model), constrains uniqueness of the items with invariant factor loadings assessed equal across groups from Model 2.

Model 4 (scalar invariance model) imposes an equality constraint on the intercepts of the items found to have invariant factor loadings in Model 2.

Finally, in *Model 5* (the structural weights invariance model) equality constraints were imposed on the structural weights among the latent variables across the groups [19].

To assess adequacy of nested models, the difference between them can be tested by subtracting the two chi-square values and testing this value against the critical value associated with the difference in degrees of freedom. Furthermore, for MASI model comparison the CFI index can also be used, because it is not influenced by sample size and model complexity and does not correlate with overall measures of fit [37]. A change in the CFI value less than or equal to −0.01 indicates that the null hypothesis of invariance should not be rejected [37].

5. Results

5.1. Data screening and descriptive summary for the total sample

Table 3 presents mean, standard deviation and correlation across selected variables. According to rules proposed in the literature [27], moderately non-normal data (univariate kurtosis < 7 and univariate skewness < 2) are acceptable. That is to say, robust standard errors provide generally accurate estimates. In our data, univariate skewness of each indicator variable was less than 1.406 in absolute value. Univariate kurtosis of each variable was less than 6.19 in absolute value. Therefore, non-normality was not a major issue for our data. Furthermore, we found no evidence of severe multicollinearity, as the mean variance inflation factor (VIF) was 3.43, a value below the suggested cut-off of 4.0 [38]. Thus the maximum likelihood estimator was used.

As indicated in Table 3, PEoU relates positively to PU ($r = 0.51$, $p < 0.01$), ATT ($r = 0.56$, $p < 0.01$) and BI ($r = 0.63$, $p < 0.01$). That is, when user's perception that ICT technology is easy to use, it affects positively to his or her perception that ICT technology will be useful, he or she is positive to adopting ICT technology, and has a positive actual intention to utilize that technology.

Table 4
TAM measurement model fit statistics for the total sample of the study ($N = 604$).

Model	χ^2	df	$\Delta\chi^2$	RMSEA	TLI	CFI	AIC
Hypothesized four factor measurement model	909.79**	146		0.093 (90% CI: 0.087–0.099)	0.909	0.923	1035.79
One factor measurement model	1041.46**	151	131.67**	0.106 (90% CI: 0.101–0.121)	0.896	0.910	1157.46

Note: χ^2:chi-square statistic.
** $p < 0.001$.

Furthermore, PU was positively related to ATT ($r = 0.79$, $p < 0.01$) and BI ($r = 0.68$, $p < 0.01$), indicating that when users perception that ICT technology will be useful, the user tends strongly to adopt IT technology, and has a positive intention to utilize that technology.

Finally ATT was positively related to BI ($r = 0.74$, $p < 0.01$) indicating that the user's positive attitude towards ICT technology encourages actually the user to utilize that technology.

Results provide support for the positive relationships found in previous research [8,18,14,10]. Furthermore, positive correlations were found between ICT knowledge and the TAM variables with the correlation being higher for PEoU ($r = 0.47$, $p < 0.01$). Finally, negative correlations were found between ICT feature demands and the TAM variables with the correlation being higher for PU of CIS ($r = -0.48$, $p < 0.01$).

5.2. Confirmatory factor analysis for the whole sample

Table 2 displays the results of the confirmatory factor analysis of the TAM variables for the total sample of clinicians ($N = 604$). All factor loadings for the items in the measurement model were greater than 0.6. The entire squared multiple correlations (SMCs) were greater than 0.60, except 3 (items PEoU4, PU6, BI1). The average variance extracted for all measures exceeded the recommended 0.5 level (0.62 for PU; 0.60 for PEoU; 0.56 for ATT and 0.55 for BI) [19].

Table 4 displays the fit statistics for the TAM measurement model. Overall, the hypothesized measurement model fits the data quite well when evaluated in terms of the recommended cut offs or the combination cut off approach [31]. In addition, the hypothesized measurement model fits the data better than a single factor model, both in terms of the fit statistics and when directly contrasted with a change in chi-square test and AIC (smaller AIC value indicate better fit of the model).

5.3. Assessment of common method bias

The basic assumption of Harman's one-factor test is that if a substantial amount of common method variance exists in the data, either a single factor will emerge or one general factor will account for the majority of the covariance among the variables. Specifically, we entered all the self-reported variables in an exploratory factor analysis with principal axis factoring and varimax rotation. Ten factors emerged with eigenvalues greater than 1 and 64.58% of the variance explained. No single factor was dominant with the first factor accounting for 12.13% of the variance. Thus, it seems that method variance is not problem for the present study.

In summary, the results suggest that the proposed factor structure presents a statistically adequate and sufficient fit to the data, all constructs in the model exhibited adequate reliability and convergent validity and no indications of severe common method variance were found.

5.4. Assessment of the structural model for the whole sample

The next step in our analysis was to consider comparative models specifying total effects (direct and indirect), complete mediation and partial mediation. The results of the specification procedure indicated that there was 84.8% probability (in terms of Akaike weights) that the best model is the one with both direct and indirect effects among TAM variables. This model revealed a good fit to the data: χ^2 (146, $N = 604$) = 909.80, $p = 0.000$; RMSEA = 0.093 (90% CI: 0.087–0.099); CFI = 0.923; TLI = 0.909; AIC = 1035.80. The second best model with probability 15.6% is the one without the path from PU to BI.

Examining the findings for direct and indirect relationships (Table 5) the model postulated that the effect of PU on BI was partially mediated by ATT. Moreover, the effects of PEoU on BI were partially mediated by both PU and ATT. Standardized direct effect of PEoU on PU was 0.53 ($p < 0.01$, two tailed). Furthermore, PEoU revealed positive direct effects on ATT (0.23, $p < 0.01$, two tailed) and BI (0.38, $p < 0.01$, two tailed) along with indirect effects on ATT (0.29, $p < 0.01$, two tailed) and BI (0.31, $p < 0.01$, two tailed). The standardized total effect (direct and indirect) of PEoU on ATT and BI was 0.60 (95% percentile confidence interval: 0.51–0.69, $p < 0.01$, two tailed) and 0.76 (95% percentile confidence interval: 0.69–0.82, $p < 0.01$, two tailed), respectively.

PU had statistically significant direct effects on ATT (0.69, $p < 0.01$) and BI (0.13, $p < 0.01$, two tailed). The standardized total effect of PU on BI was 0.49 (95% percentile confidence interval: 0.39–0.60, $p < 0.01$, two tailed). Finally, the direct effect of ATT on BI was 0.53, (95% percentile confidence interval: 0.36–0.67, $p < 0.01$, two tailed).

In summary, the proportion of variance (squared multiple correlations) in PU, ATT and BI that was explained by the collective set of predictors was 29% (95% CI: 0.20–0.39), 70% (95% CI: 0.63–0.78), 83% (95% CI: 0.76–0.91) respectively.

5.5. Inclusion of external variables in the model

The model that included the external variables revealed a good fit to the data: χ^2 (183, $N = 604$) = 987.468, $p = 0.000$; RMSEA = 0.085 (90% CI: 0.081–0.091); CFI = 0.921; TLI = 0.910; AIC = 1125.47.

Medical professionals' ICT feature demands has a direct negative effect on PU [-0.43, $p < 0.001$, two tailed; 95% CI: (-0.49) to (-0.36)] (see Fig. 2). The standardized total (direct and indirect) effect of ICT feature demands on ATT and BI were -0.30 [95% CI: (-0.36) to (-0.24)] and -0.21 [95% CI: (-0.27) to (-0.15)], respectively.

On the other hand medical professionals' ICT knowledge had a direct positive effect on PEoU (0.49, $p < 0.001$) (see Fig. 2). The total standardized effect of ICT knowledge on PU, ATT and BI were 0.25 (95% CI: 0.21–0.30), 0.29 (95% CI: 0.24–0.34), and 0.37 (95% CI: 0.31–0.42) respectively. In other words, due to both direct (unmediated) and indirect (mediated) effects of ICT knowledge on BI when

Table 5
Standardized direct and indirect effects and associated 95% confidence intervals in parenthesis. The upper and lower bounds of the 95% confidence interval (shown in parentheses) were based on the findings from a bootstrapping analysis using the percentile method.

Predictor	Perceived usefulness (PU)		Attitude (ATT)		Behavioral intention (BI)	
	Direct effect	Indirect effect	Direct effect	Indirect effect	Direct effect	Indirect effect
Outcome						
PEoU	0.53* (0.45–0.62)	–	0.23* (0.14–0.32)	0.29* (0.28–0.45)	0.38* (0.27–0.46)	0.31* (0.29–0.46)
PU	–	–	0.69* (0.60–0.78)	–	0.13* (0.05–0.29)	0.25* (0.24–0.48)
ATT	–	–	–	–	0.53* (0.36–0.67)	–

* $p < 0.01$.

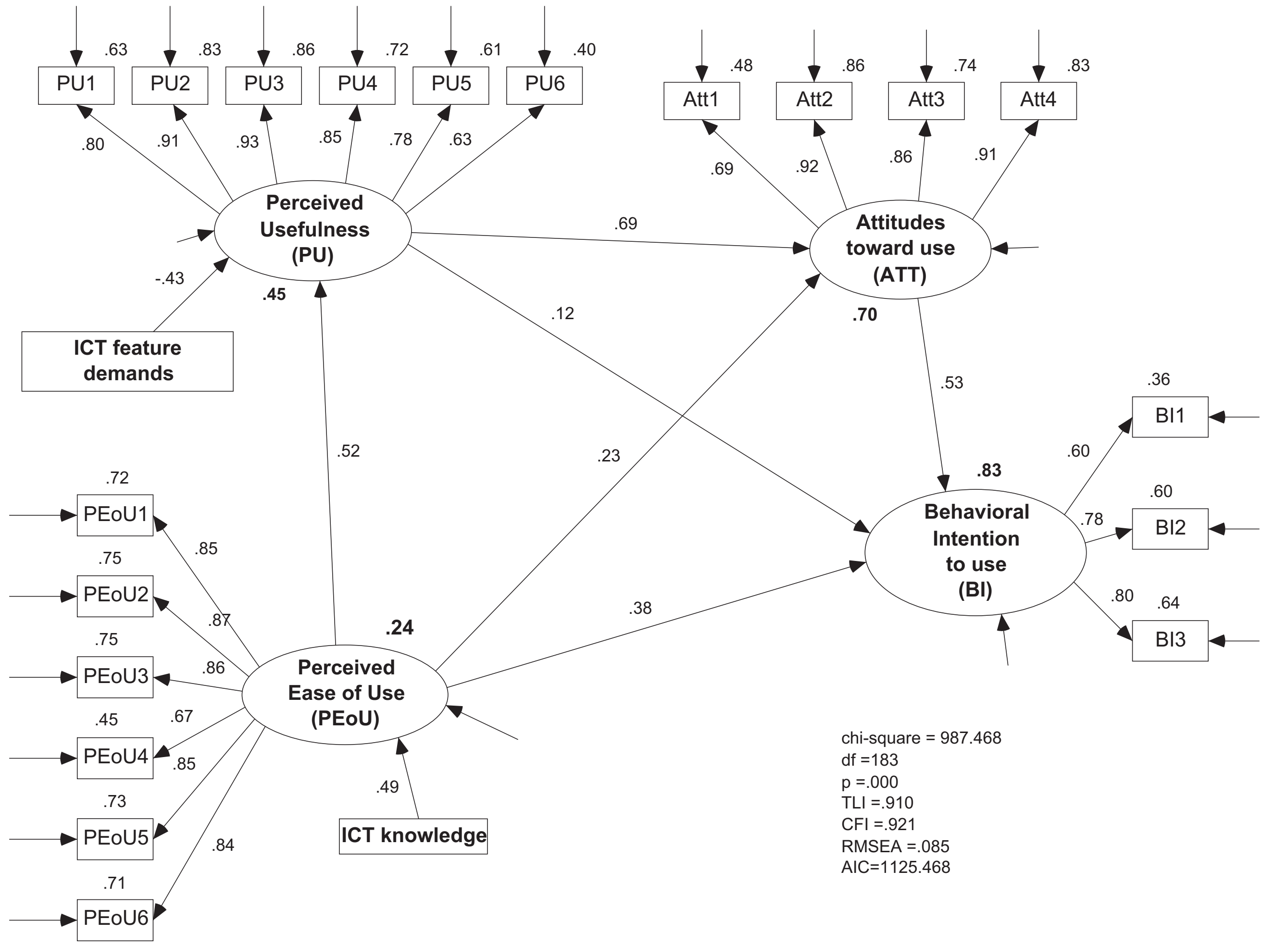

Fig. 2. Structural model (standardized results). Circles represent latent factors; boxes represent indicators. Casual effects are given by arrows connecting circles. Bold numbers over circles represent variance explained. Disturbance and measurement error effects are omitted for clarity.

ICT knowledge goes up by 1 standard deviation, BI goes up by 0.37 standard deviations. Medical professionals' ICT feature demands explain an additional 16% of the PU variance, while ICT knowledge explains 24% of the variance in PEoU. Furthermore all paths among the TAM variables remained statistically significant at the 0.001 level.

5.6. Multi-group analysis of structural invariance (MASI)

When performing multi-group analysis, the sample size of the groups being compared should be roughly equal [21]. In our sample we could test for specialty group differences only between surgeons ($n = 215$) and pathologists ($n = 233$), as these groups provide adequate sample size. The mean age in years was 37.6 for surgeons and 36.2 for pathologists. No statistical significant differences between surgeons and pathologists were found in terms of age [$t(419) = 1.75$, $p = 0.81$], ICT knowledge[$t(446) = -0.335$, $p = 0.738$], ICT feature demands [$t(446) = -1.389$, $p = 0.165$] and hours using a PC per week [$t(446) = -1.07$, $p = 0.292$]. However, surgeons reported more tenure ($M = 5.27$ years, SD = 6.5 years) compared to pathologists ($M = 3.99$ years, SD = 4.92 years) [$t(446) = 1.99$, $p = 0.047$]. Finally, the chi-square test showed that there are differences between the 2 groups in terms of gender ($\chi^2 = 17.327$, $p = 0.000$). In the surgeons group there were 162 male and 53 female participants while in the pathologist group there were 132 males and 101 females.

Before conducting MASI, we examined model-data fit and parameter estimates for the entire sample ($n = 448$). The hypothesized structural model revealed a good fit to the data: χ^2 (146, $N = 448$) = 705.03, $p = 0.000$; RMSEA = 0.093 (90% CI: 0.086–0.099); CFI = 0.923; TLI = 0.910; AIC = 831.03. These results suggest that the structural model was appropriately specified, a proper solution was obtained and the solution fit the entire sample adequately. The completely standardized item-factor loadings for PU, PEoU, and BI measurements were high (from 0.57 to 0.92) and statistically significant. All items had reliability scores (R^2) ranging from 0.51 to 0.87, indicating good item reliability. Thus, all measurement items for the structural model were valid and reliable measures of their theoretical construct.

To test the structural invariance across medical specialty, we conducted a multi-group analysis of structural invariance. First we tested Model 1 (the configural invariance model) with no equality constrains for both groups. This model revealed an adequate fit to the data: χ^2 (292, $N = 448$) = 1088.23, $p = 0.000$; RMSEA = 0.078 (90% CI: 0.073–0.083); CFI = 0.901; TLI = 0.903; AIC = 1340.23 (Table 6), thus supporting the configural invariance.

Model 2 (the metric invariance model) also displayed an adequate fit to the data (Table 6). Examination of the probability level associated with the chi-square test for each item loading constraint separately, showed that the three item loadings associated with the items PU2, PU3, PU4, were not invariant across surgeons and pathologists, indicating the condition of partial metric invariance.

In Model 3 (measurement error invariance) equality constraints were added on the 16 item loadings that were found invariant in Model 2 and on their respective error terms. Model 3 displayed an adequate fit to the data (Table 6). The chi-square difference test results showed that 2 out of the 16 equality constraints imposed on the error terms were non-invariant. The non-invariant error

Table 6
Goodness of fit for the physician specialty (surgeons vs. pathologists) invariance models ($N = 448$). Numbers in parentheses indicated the models compared.

Structural model	χ^2	df	$\Delta\chi^2$	RMSEA	TLI	CFI	AIC
1. Configural invariance model	1088.23, ns	292	–	0.078 (90% CI: 0.073–0.083)	0.903	0.901	1340.23
2. Metric invariance model	1098.01, ns	304	$9.781^{*\ (1-2)}$	0.077 (90% CI: 0.072–0.081)	0.888	0.901	1326.01
3. Measurement error invariance model	1117,37, ns	318	$29.136^{*\ (1-3)}$ $19.355^{*\ (2-3)}$	0.075 (90% CI: 0.070–0.080)	0.902	0.900	1317.37
4. Scalar invariance model	1138.03, ns	331	$49.799^{*\ (1-4)}$ $40.017^{*\ (2-4)}$ $20.663^{*\ (3-4)}$	0.074 (90% CI: 0.069–0.079)	0.896	0.899	1312.03
5. Structural weights invariance model	1146.22, ns	337	$8.39^{*\ (4-5)}$	0.073 (90% CI: 0.069–0.078)	0.897	0.899	1308.42

* $p > 0.1$.

terms were associated with items PU1 and PEoU1. Thus, partial measurement error invariance was demonstrated.

Model 4 (scalar invariance model) also displayed an adequate fit to the data (Table 6). The chi-square test revealed the tenability of all of the item intercept constraints imposed on the model, except for the constraints associated with items PEoU1 PEoU2 and PEoU3. Hence, partial scalar invariance was supported.

With respect to model differences, the chi-square difference tests showed that Model 2 was significantly better than Model 1 and that Models 3 and 4 were significantly better than Model 2. Furthermore, Model 4 was significantly better than Model 3 (Table 6). Since Model 4 (the scalar invariance model) had the best fit, it was used for testing the structural weights.

Model 5 (the structural weights invariance model) also displayed an adequate fit to the data (Table 6). Examination of the probability level associated with the chi-square test for each structural weight among the latent variables constraint separately, showed that the structural weight between PEoU and PU was not invariant across surgeons and pathologists, indicating the condition of partial structural invariance. In Table 7 we present the standardized structural weight for both groups.

For surgeons, the proportion of variance (squared multiple correlations) in PU, ATT and BI that was explained by the collective set of predictors was 51% (95% CI: 0.34–0.66), 71% (95% CI: 0.52–0.86), and 93% (95% CI: 0.82–0.98), respectively. For pathologists, the proportion of variance in PU, ATT and BI that was explained by the collective set of predictors was 21% (95% CI: 0.10–0.37), 72% (95% CI: 0.61–0.81), and 81% (95% CI: 0.68–0.94), respectively.

Including the ICT feature demands variable to Model 5 (the structural weights invariance model) explained an additional 11% and 29% of the variance in PU for surgeons and pathologists respectively. The percentage of variance explained for PEoU when ICT knowledge was included in Model 5, was 21% and 19% for surgeons and pathologists respectively. While the regression weight from ICT knowledge to PEoU was invariant across specialties, the regression weight from ICT feature demands to PU was not invariant (Table 7).

6. Discussion

In the present study the largest sample size ever tested was used in order to explore empirically the application of the TAM in the health sector. Structural equation modeling (SEM) and multi-group analysis of structural invariance (MASI) analyses were conducted with a sample of 604 clinicians, including 534 physicians from 13 main state hospitals and one private hospital in Greece. Both SEM and MASI were used in parallel for the first time in order to test TAM in the health sector. Measurement error is minimized in these methods, through the use of multiple indicators of latent variables prior to testing model fit. Furthermore, the use of SEM in this study allowed both the direct and indirect effects to be analyzed, hence allowing the possibility of achieving a more accurate model.

In our analyses we initially tested the standard TAM, in order to facilitate the comparison for future studies and then we tested an extended TAM model. We need to stress however, that we assessed attitudes and beliefs regarding the use of clinical information systems (CIS) rather than attitudes and beliefs directed towards CIS itself, since clinicians might hold a positive view about CIS, without being favorably disposed towards its use. Our results support previous studies in TAM, which suggest that clinicians' attitudes towards the use of CIS are related to their intention to use such systems. In addition, attitudes towards CIS are influenced by: (a) clinicians' belief that using CIS will increase their job performance (perceived usefulness-PU) and (b) clinicians' belief that a CIS is free of effort (Perceived Ease of Use-PEoU). Furthermore, PU of CIS is influenced by PEoU (see Fig. 2).

We successfully extended the TAM (in terms of model fit) by including two external factors relevant to clinicians, namely self-reported information and communication technology (ICT) knowledge and self-reported ICT feature demands as antecedents of PEoU and PU respectively. Finally, we found evidence for the moderating effect of physicians' specialty.

Although recent empirical research suggests that TAM is a good predictor of clinician behavioral intent to accept technology [6,12,20], more research is needed to establish confidence in the relationships among TAM variables, when the theory is implemented in the health care. For example, Holden and Karsh [6], in their recent meta-analytic review concerning the application of TAM in health care, found that in studies with physician samples the PEoU-BI relationship was non-significant. However, the majority of these studies had sample sizes less than 90 individuals raising concerns about the statistical power of the model's parameter estimates. Our results clearly point to a direct effect of PEoU on BI. The standardized direct effect of PEoU on BI was $\beta = 0.37$.

Table 7
Structural paths for physician specialty (standardized estimates). The upper and lower bounds of the 95% confidence interval (shown in parentheses) were based on the findings from a bootstrapping analysis using the percentile method.

Structural path	Specialty		
	Surgeons ($n = 215$)	Pathologists ($n = 233$)	$\Delta\chi^2$
PEoU → PU	0.72* (0.59–0.81)	0.46* (0.28–0.61)	4.10, ($p = 0.03$)
PEoU → ATT	0.28* (0.15–0.41)	0.27* (0.16–0.40)	4.098, ($p = 0.535$)
PEoU → BI	0.33* (0.21–0.47)	0.32* (0.19–0.43)	3.091, ($p = 0.543$)
PU → ATT	0.62* (0.45–0.78)	0.69* (0.57–0.79)	0.153, ($p = 0.696$)
PU → BI	0.23* (0.10–0.43)	0.25* (0.08–0.45)	7.975, ($p = 0.241$)
ATT → BI	0.48* (0.26–0.69)	0.46* (0.27–0.64)	3.046, ($p = 0.385$)
ICT feature demands → PU	−0.45* [(−0.56)–(−0.33)]	−0.49* [(−0.62)–(−0.34)]	13.17, ($p = 0.04$)
ICT knowledge → PU	0.46* (0.36–0.56)	0.44* (0.35–0.52)	8.86, ($p = 0.354$)

* $p < 0.001$.

We found that the standardized total effect (direct and indirect) of PEoU on BI was $\beta = 0.76$, which is higher than the standardized total effect of PU on BI ($\beta = 0.49$). Clearly, clinicians place more importance to the intrinsic aspects of CIS (captured by PEoU) compared to its extrinsic aspects (captured by PU). In other words, PEoU will affect the use of CIS when the intrinsic character of the technology contributes to the actual outcome of its application. This is in line with studies proposing that the effect of PEoU on intentions is stronger in the early stages of learning and behavior [1]. "Easy to use" attributes of a clinical information system are developed by IT technicians and among other attributes are related to interface characteristics such as user friendliness, operational simplicity, effective data retrieval, manipulation and presentation etc. as well as operational characteristics such as data organization and sharing, fast access, data combination and querying etc. An "easy to use" system is considered to be less time-consuming and this is one of the factors influencing clinician's intention to use ICT [4]. On the other hand attributes related to the "usefulness" are worked on mostly by clinicians and refer to the medical knowledge which is embedded in the system and being continuously updated. Hence "usefulness" is related to data sufficiency and availability in terms of quantity and quality, clarity, accuracy etc. Clinical data may be supplied in the system by clinicians for global use.

Hospital and IT managers could turn this into advantage, in order to encourage the frequent use of a new ICT system. Not only during the first stages of systems installation and implementation but also during training, emphasizing tactfully more in the systems "easy of use" rather than its "usefulness" could be the key, in order to achieve better personnel involvement. In addition, an "easy to use" system is considered as less time-consuming and this is one of the factors influencing clinician's intention to use ICT [4].

Furthermore, our research was conducted in settings where CIS are not individually financed by clinicians. This finding implies that although PU is an important determinant of the acceptance of a CIS, when clinicians are not paying for the cost of the technology, or if the decision to pay for the technology has already been made, PEoU may be a strong catalyst fostering the acceptance of CIS.

Results showed that extending the TAM by including medical professionals' perceived ICT knowledge and perceived ICT feature demands as antecedents of PEoU and PU respectively, revealed a good fit to the data. Both factors are relevant to clinicians and pertain to user personal characteristics. We found that medical professionals' ICT knowledge, that is, how much knowledge clinicians perceive to have about ICT, had a direct positive effect on PEoU ($\beta = 0.49$). Medical professionals' ICT feature demands that is, how sophisticated ICT must be before clinicians would be willing to use them, had a direct negative effect on PU ($\beta = -0.43$).

We found no significant direct effects of the two external factors on BI; stated differently, the TAM constructs fully mediate the effects of the external factors on BI. The implication of these findings is that our research contributes to a better understanding of the antecedents of PU and PEoU in health care contexts, thus providing useful information to practitioners in terms of which levers to pull in order to affect these beliefs and through them the use of CIS.

Although the current generation of trainees and young clinicians has never lived in a world without pervasive technology, ICT knowledge is different from simply using ICT. For example in our sample clinicians have on average a rather general appreciation of the distinction between pairs of ICT concepts (mean of ICT knowledge = 2.26) but could not define it. This implies a low confidence in understanding basic ICT concepts, which in turn reflects insufficient training. Our results suggest that enchasing clinicians' confidence on ICT knowledge through appropriate training, will result in higher beliefs that using CIS will be rather free of additional efforts. Stated differently, general ICT knowledge may help clinicians' transition into using more sophisticated CIS by improving their ease of use or comfort with learning and using CIS systems.

In the same vein, our results suggest that clinicians' beliefs that using CIS will increase their job performance (i.e. PU) are negatively related to clinicians' ICT features demand. This finding confirms previous studies suggesting that medical health professionals are more likely to adopt CIS that are perceived as compatible with clinicians' current work processes [5,39]. What is more, this finding is in line with growing interest in the "Fit between Individuals, Task and Technology" (FITT) framework, as a critical need for successful CIS design [6]. Under the FITT framework, IT adoption in a clinical environment depends on the fit between the attributes of the individual users, attributes of the technology, and attributes of the clinical tasks and processes.

In addition, the FITT framework clearly implies potential differences in the strength of the relationships between criterion and predictor variables in the TAM model, when different medical specialties are considered. Medical diagnosis and treatment is a complex work process and existing evidence point to physicians' specialty differences in the implementation of medical practice. In the present research, we tested for differences between surgeons ($n = 215$) and pathologists ($n = 233$) using MASI analysis. Our results provide initial evidence for the moderating effect of physician's specialty in PEoU–PU and ICT feature demands-PU relationships. Specifically, we have found that for surgeons it is more important the CIS to be easy to use in order to be considered as useful compared to pathologists (see Table 7, the PEoU → PU path).

Furthermore, surgeons seem to be less demanding in ICT features in order to perceive CIS as useful compared to pathologists (see Table 7, the ICT feature demands → PU path). These findings indicate that design and training sessions should explicitly consider medical specialty as an important factor in the adoption of CIS.

This study raises implications for the hospital administrators. The predictive power of attitude towards usage indicates the need to develop positive attitudes among health care professionals, to ensure professionals' acceptance and continued use of CIS applications. Finally, although PU and PEoU have been found to predict behavioral intent, they do not remain static. Healthcare professionals who perceive CIS to be useful and easy to use may soon experience limitations if they do not participate in continuous professional development to keep abreast with more advanced skills and knowledge on the use of CIS. For example, in our study we have found that older clinicians have lower levels of perceived ICT knowledge ($r = -0.14$, see Table 2), and that the longer the tenure of clinicians the lower the levels of perceived ICT knowledge ($r = -0.24$, see Table 2). This suggests the importance of clinician's professional development towards increasing the perceived ICT knowledge; ICT knowledge has an indirect effect on behavioral intention to use CIS. In addition, it is plausible that the scheduled rotation of clinicians among different hospitals could develop further clinicians' perceived ICT knowledge.

6.1. Study limitations

Although care has been taken to ensure that the methodology in this study is sound, there are several limitations that warrant further research. First, this is a survey, not an audit of actual practice, and thus data are self-reported. Furthermore, our cross-sectional design prevents us from studying causal relationships among our variables. Future studies should use longitudinal data to rigorously assess the stability of the identified relationships over time.

Second, our study concentrated on Greek hospitals, where the decision to pay for the technology has already been made. Caution should therefore be exercised in generalizing these findings to non-comparable populations. Consequently, future studies might want to consider the implications of our work for different populations.

A third limitation arises from the analysis of healthcare professional's technology acceptance decisions, regarding clinical information systems in general, and not a specific health information system. Thus, our readers should be cautious in extrapolating the results to other groups of health information systems.

A forth limitation is the fact that the proportion of variance (squared multiple correlations) in PU, ATT and BI that was explained in this study by the collective set of predictors was 29%, 70% and 83% respectively, leaving room for further improvement, especially for the PU construct. In the pursuit of parsimony, it is possible that this study has excluded other variables that may impact significantly on technology acceptance in health care. Furthermore, the measurement of the external variables (ICT knowledge and feature demands) were based on Cork's instrument [9], developed in 1998. Considering the all the changes in IT over the past 12 years, future research should consider using more up-dated scales.

A final limitation concerns the use of behavioral intention as a measure for actual use, as this may have weakened and contributed to the loss of explanatory power of the model in this study. Although intention to use technology as a construct has been reported to be a suitable proxy for actual technology, still there is a question as to whether the TAM can act as an accurate predictor of actual usage rather than behavioral intention to use.

These limitations represent, in any case, opportunities to advance in our efforts to better understand CIS adoption in the health care.

7. Conclusions

TAM is a well known theory of technology acceptance and existing evidence suggests that the theory generally holds in clinical contexts. However, opportunities still exist for researchers to enhance TAM capabilities as a useful theoretical tool in the health care. In this article TAM was replicated. The largest sample size ever tested with TAM in the health sector (604 clinicians) was used, including 534 physicians from 13 main state hospitals and one private hospital in Greece. Results of structural equation modeling analysis, confirm the predictive power of TAM, providing support for the positive relationships found in previous research projects in health care. Specifically, in the present study, positive relationships were found between ATT and BI and between PEoU and PU. Both PEoU and PU were positively related to ATT. Furthermore, PU was positively related to BI. Finally, our results point to a positive relationship between PEoU and BI, a relationship that has been found to be inconsistent in some of the previous TAM studies conducted in the health care [6]. Overall, the percentage of variance explained in BI accounted for by the predictors in the model was 83% and it is among the largest ever found in health care [6].

In addition, medical staffs' ICT knowledge and ICT feature demands were tested as external variables and physicians' specialty specific differences in TAM were introduced (i.e. pathologists and surgeons). We have found that both ICT knowledge and ICT feature demands explain an additional variance in PEoU and PU respectively. However, their effects on BI are fully mediated by the TAM variables. Finally, we have found that physicians' specialty moderates the PEoU–PU and ICT feature demands-PU relationships.

In conclusion, our findings make a contribution to the literature by replicating, explaining and advancing the TAM, whereas theory is benefited by the addition of external variables.

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Appendix A

ICT knowledge: items and results of factor analysis with geomin rotation ($N = 604$).

	1
CW 1 – Client–server	0.795
CW 2 – Field–record	0.758
CW 3 – Electronic mail–electronic bulletin board	0.750
CW 4 – Free text–coded data	0.804
CW 5 – Database–knowledge base	0.809
CW 6 – Data in memory – data on disk	0.873
CW7 – Digital–analog	0.845
CW8 – Relational database–flat-file database	0.729
CW9 – Full-text database–bibliographic database	0.841
CW10 – Mainframe computer–Personal computer	0.810
CW11 – Images–graphics	0.893
CW12 – CD-ROM – floppy disk–hard disk	0.950
CW13 – Hardware–software	0.959
CW14 – Forward chaining–backward chaining	0.682
CW15 – Sensitivity–positive predictive value	0.762

Note: 1–3 scale: 1 = I do not understand the distinction at all, 2 = I have a general appreciation of the distinction but could not define it, 3 = I can define the distinction precisely). The WLSMV estimator in Mplus v.5.21 was used to estimate factor loadings.

Appendix B

ICT feature demand: results of factor analysis with geomin rotation ($N = 604$).

	1	2
SCF1 – Explain rationale for patient care advice	0.744	–
SCF2 – Provide accurate treatment recommendations	0.799	–
SCF3 – Make accurate diagnoses	0.413	–
SCF4 – Quantify the uncertainty of recommendations	0.456	–
SCF5 – Provide multiple alternative patient care recommendations	0.375	0.329
SCF6 – Allow browsing of information as well as providing specific advice	0.580	0.386
DCU1 – Take patient preferences into account when giving advice	–	0.436
DCU2 – Display images in less than 30 s	–	0.765
DCU3 – Respond to queries in less than 5 s	–	0.822
DCU4 – Allow access at any place in clinical setting	0.381	0.544
DCU5 – Allow implementation without any change in existing clinical routines	0.327	0.606
DCU6 – Function without any down-time	0.354	0.593
DCU7 – Allow interaction without use of keyboard	–	0.617
DCU8 – Be learnable in less than 2 h	–	0.671
DCU9 – Allow data entry in user's own words without requiring special codes	–	0.596

Note: 1–4 scale: 1-"Vitally necessary" to 4-"not necessary". Loadings below 0.30 are not shown. The WLSMV estimator in Mplus v.5.2 was used to estimate factor loadings. SCF = sophisticated computer features; DCU = demand for computer usability.

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