Electronic Health Record Portals adoption: Empirical model based on UTAUT2

Jorge Tavares[1*§], Amélia Goulão[1*], Tiago Oliveira[1*]

[1]NOVA IMS, Universidade Nova de Lisboa, Portugal

[*]These authors contributed equally to this work
[§]Corresponding author at: NOVA IMS, Universidade Nova de Lisboa, Campus de Campolide, 1070-312 Lisboa, Portugal. Tel.: +351 91 7330943

Email addresses:
JT: tavares.jorge@gmail.com
AG: amelia.goulao@gmail.com
TO: toliveira@novaims.unl.pt

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A New Application of UTAUT2 Model

Jorge Tavares[1*§], Amélia Goulão[1*], Tiago Oliveira [1*]

[1] NOVA IMS, Universidade Nova de Lisboa, Portugal

*These authors contributed equally to this work

[§]Corresponding author at: NOVA IMS, Universidade Nova de Lisboa, Campus de Campolide,

1070-312 Lisboa, Portugal. Tel.: +351 91 7330943

Email addresses:

JT: tavares.jorge@gmail.com

AG: amelia.goulao@gmail.com

TO: toliveira@novaims.unl.pt

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Abstract

Background: The future of health care delivery is becoming more citizen-centred, as today's user is more active and better informed. Governmental institutions are promoting the deployment and use of online services such as Electronic Health Record (EHR) portals. This makes the adoption of EHR portals an important field to study and understand.

Objective: The aim of this study is to understand the factors that drive individuals to adopt EHR portals.

Methods: This study applies the extended unified theory of acceptance and usage technology (UTAUT2) to explain patients' individual adoption of EHR portals. An online questionnaire was administered. We collected 386 valid responses.

Results: The statistically significant drivers of behavioural intention are performance expectancy ($\hat{\beta}$=0.17; $p<0.01$), effort expectancy ($\hat{\beta}$=0.17; $p<0.01$), social influence ($\hat{\beta}$=0.10; $p<0.05$), and habit ($\hat{\beta}$=0.37; $p<0.001$). Habit ($\hat{\beta}$=0.28; $p<0.001$) and behavioural intention ($\hat{\beta}$=0.24; $p<0.001$) are the statistically significant drivers of technology use. The model explains 52% of the variance in behavioural intention and 31% of the variance in technology use.

Conclusions: By testing an information technology acceptance model, we are able to determine what is more valued by patients when it comes to deciding whether to adopt EHR portals or not.

Keywords

UTAUT2; technology adoption; e-health; health care consumers; electronic health records

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INTRODUCTION

Our study focuses on a specific type of e-health technology, the electronic health record (EHR) portals, which bring clear benefits for both patients and healthcare providers and has received great attention at the governmental level worldwide [1-3]. In the US the support given to EHRs, via meaningful use program, led the federal government to commit unprecedented resources to support adoption and use of EHRs through incentive payments totalling $27 billion over 10 years, or as much as $44,000 (through Medicare) and $63,750 (through Medicaid) per physician [4-6]. EHR portals are an important topic not only in the US, but also in Europe, where there is a new trans-European initiative, the European Patients Smart Open Services (epSOS), promoted by the EU Commission [3]. EpSOS concentrates on developing a practical e-health framework and Information and Communication Technology (ICT) infrastructure that will allow secure access to patient health information, including EHR amongst different European countries [3].

The aim of this study is to understand the factors that drive individuals to adopt EHR portals. We apply the extended unified theory of acceptance and use of technology (UTAUT2) to propose a model to explain individuals' behavioural intention and use of EHR portals, from the patient (consumer) point of view.

The structure of this paper is the following. In the next section the concept of EHR portals is explained, as is the theoretical background used in this study, and there is a discussion of earlier research. In the second part of the paper the research model, hypotheses, and the methodology are presented. Then, the results of measurement and the structural model are presented. Finally, the theoretical and managerial implications are exposed and possible future research arising from this study is suggested, followed by conclusions.

The concept of EHRs portals

An EHR portal is a web based application that combines an EHR system and a Patient Portal whereby patients can interact with their healthcare providers (e.g., schedule medical appointments, send messages to their physicians, request prescription refills online), and access their medical records and medical exams results [7-12]. By doing these tasks on the EHR portal they avoid unnecessary travelling to the healthcare centre and they can access their medical information in a structured manner anywhere through an internet connection [1, 3, 11]. EHR portals will also bring clear benefits to the healthcare providers, who can communicate more effectively with patients and reduce administrative costs by implementing on-line services previously sought off-line [2, 8, 13].

In the US the meaningful use program, a three stage program, started with the aim of achieving good results within EHRs use. A good example is a cohort study about primary care physicians in New York State [14]. This study showed that physicians that were using EHRs and adhering to the meaningful use program had fewer patient visits, resulting in a more effective management of resources and reduction of unnecessary patient visits by 17% [14]. Patients also strongly believed just before the implementation of the meaningful use program that the most critical advantage of EHR was the effective reduction of errors in the medical records compared to the paper versions [1], but confidentiality concerns over the use of the information on their EHRs were also reported [1]. A recent published study, following meaningful use implementation showed that patients whose clinicians used EHRs were generally more likely to believe EHRs would improve healthcare quality and less concerned about privacy risks than those whose doctors did not use EHRs [15]. The overall reduction in privacy concerns by the patients engaging the meaningful use program was 7% [15]. After meaningful use stage 1, a stage with great focus on healthcare provider's use of EHR [3, 4, 14], new guidelines were issued by the Center for Medicare & Medicaid Services (CMS), called Stage 2 meaningful use [11, 16]. These guidelines require that the eligible professionals and hospitals engaged in Medicare and Medicaid EHR Incentive Programs must give their patients secure online access to their health information, including EHRs [10, 11, 16]. In the US most of the health institutions were not providing access to patients' EHRs via Patient Portals [10, 11, 16]. According to the new guidelines the healthcare institutions must not only implement EHR portals, but also demonstrate their effective use by patients, with more than 5% of the patients accessing their EHR via the Portal [3, 10, 11, 16]. Recent reports point out that EHR access by the patients is increasing in the US [6].
EHR Portals have been implemented not only in the US but also in Europe [3]. In Portugal a National Health Service (NHS) Portal was implemented, but its success was limited with only approximately 7% of potential users registered and a low level of global use [3]. Among several features the NHS Portal would allow the patients to make appointments with their NHS family physician, access their medical records, obtain e-prescriptions renewals for chronic diseases, and update their personal records [3]. The Portal is now undergoing an upgrade to allow new features to be included, such as the possibility to share information with other entities outside the NHS and also with other European countries, meeting the epSOS requirements [3]. Private healthcare providers in Portugal also invested in EHR

Portals. One specific private provider, with a large number of clinics and hospitals in Portugal developed, an EHR Portal (My Cuf) [3, 8, 17], that in addition to all the traditional features, such as on-line appointment requests, developed a system that allows the patients to receive via web or a specific mobile app, exam results in real time, with the exception of those not allowed by the physician [3, 8, 17]. Most of the exams are delivered on-line, except if the patient requires a paper version. The provider states that with this measure the patients now have access to their EHRs on- line, without using paper versions, increasing the convenience for the patients and the effectiveness for the healthcare provider [3, 8, 17].

E-health adoption models

Not many studies have been made relating health, information technology, and individual adoption models, and the majority that do exist have focused more on the healthcare professionals' use of e-health technologies and less on the patients' perspective [1, 18]. Even though this area of research is not widely explored, some studies have been made to investigate these factors and some conclusions can be taken, as shown in Table 1.

Most of the research in this area [18-20] uses the technology acceptance model (TAM) or even more often TAM with extensions in order to help explain behavioural intention or use behaviour. In the case of TAM alone, there is an example of a qualitative study by Jung and Loria [19] to determine the reasons for adoption of e-health platforms by the patients. Currently what is more common to find in the literature is the use of TAM with other models. For instance, Wilson and Lankton [18] studied TAM with two different models (motivational model, and integrated model) in order to predict patients' behavioural intention on e-health services aimed to the patient. Lemire et al. [20] also used TAM to predict patients' use, but extended the model by incorporating other constructs: quality of information, trust in the information, importance given to the opinions of health professionals, importance given to health information in media, and concern for one's health. Kim and Park [21] developed an extended version of TAM that incorporated, besides, the theory of planned behaviour, the health belief model (HBM). The fact that TAM is still being used frequently is the example of a very recent study by Hoque et al. [22], in which the authors extend TAM to include privacy and trust to study the factors that influence the adoption and use of e-health applications for patients in a developing country. Apart from the frequently used extended versions of TAM, other authors have applied other approaches. A good example is the study by Angst and Agarwal [1] who integrated the individual's concern for information privacy (CFIP) framework with the elaboration likelihood model (ELM) to examine attitude change and likelihood adoption of an EHR system by the patients. Another example is the development of a new theoretical framework by Lemire et al. [23] to study how patient empowerment may influence the adoption of web based services for the patients .

Table 1 summarizes some of the studies made in the area of e-health services, the theory or the theories behind the studies, the dependent variable that is being explained by the study, and the most important findings. The target population in all studies was patients.

Table 1 - E-Health adoption models

Theory	Dependent variable	Findings	Reference
TAM, motivational model (MM), integrated model (IM)	e-health behavioural intention	▪ PEOU (TAM), PU (TAM), Intrinsic Motivation (IM) and Extrinsic Motivation (MM) have significant positive influence on behavioural Intention. ▪ IM does not have a better performance than TAM or than MM when predicting behavioural Intention.	[18]
Elaboration likelihood model (ELM), concern for information privacy (CFIP)	EHR behavioural intention	▪ Positively framed arguments and Issue Involvement generate more favourable attitudes toward EHR behavioural intention. ▪ CFIP is negatively associated with likelihood of adoption.	[1]
TAM (qualitative study)	E-health services behavioural Intention	▪ PU seemed to be important. ▪ PEOU did not seem to be an issue. ▪ Although Experience is not a TAM construct, it seemed to have influenced behavioural Intention.	[19]
TAM, plus several other constructs	Internet use behaviour as a source of information	▪ PU, importance given to written media in searches for health information, concern for personal health, importance given to the opinions of physicians and other health professionals, and the trust placed in the information available are the best predictors of use behaviour.	[20]
Personal empowerment	Internet use behaviour as a source of information	▪ There are 3 types of attitudes encouraging Internet use to seek health information: Professional logic, Consumer Logic, and Community Logic.	[23]
Extended TAM in Health Information Technology (HIT)	HIT behavioural intension	▪ PU, PEOU and perceived threat significantly impacted health consumer's behavioural intension.	[21]
TAM, Trust and Privacy	Intention to adopt e-Health	▪ PEOU, PU and trust are significant predictors.	[22]

Extended unified theory of acceptance and usage technology (UTAUT2)

In 2003 Venkatesh et al. [24] reviewed eight different models and combined different elements of them into the unified theory of acceptance and use of technology (UTAUT), including elements from TAM, from which incorporates the concept of Perceived Usefulness

(PU) as performance expectancy and Perceived Ease of Use (PEOU) as effort expectancy [24]. Apart from these two constructs from TAM, UTAUT also uses two other constructs, social influence and facilitating conditions [24]. These constructs were moderated by age, gender, experience, and voluntariness of use. A relevant finding that justifies the use of UTAUT over other models including TAM is that the R^2 obtained with UTAUT was greater than those of any of the individual models [24]. The advantages of UTAUT over TAM and other models have been demonstrated successfully over time [25]. Although UTAUT provides better results than TAM and other adoption models [24, 25] , the focus of UTAUT is the employee technology acceptance at the individual level [24, 25], which is not the focus of our paper because our target group is health care consumers. Preferably, we need a model adapted to the consumer use context, and in this particular field, UTAUT2 was developed with this aim, obtaining very good results [25]. This new model includes the same four UTAUT constructs plus three new constructs that are consumer specific: hedonic motivation, price value, and habit [25]. The constructs are now moderated only by age, gender, and experience. The moderator voluntariness of use was dropped since the target population was not obliged to use the technology. Compared to UTAUT, the three new consumer specific constructs proposed in UTAUT2 have produced a substantial improvement in the variance explained in behavioural intention (from 56% to 74%) and technology use (from 40% to 52%) [25].

METHODS

To explain individuals' behavioural intention and technology use of EHR portals, the model proposed herein applies the UTAUT2 model to a health related area (Figure 1). We follow the model proposed by Venkatesh et al. [25] to understand if it can also be applicable to an EHR portals environment. For this we propose the same constructs that exist in the original model of UTAUT2 and make some adjustments to the hypotheses in order to obtain a better fit to the EHR portals environment. Experience was not measured since our questionnaire was applied at just one moment in time.

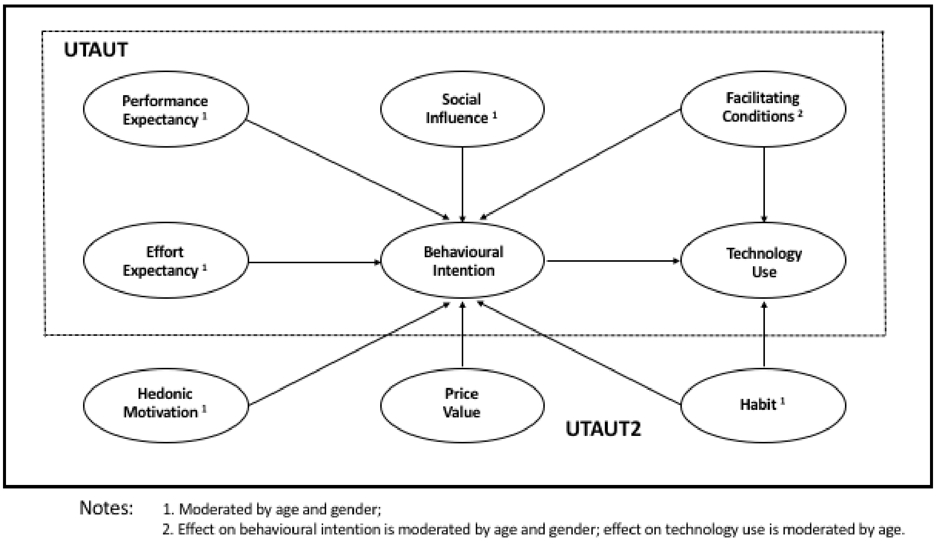


Figure 1 - Research model adapted from Venkatesh et al. [25]

UTAUT2 Model

In our study we followed the same rationale used by Venkatesh et al. [25] in their original paper to establish the hypotheses (including the moderators), and for each construct we evaluated their application concerning the current study's main topic (EHR portals). According to the extensive study performed by Venkatesh et al. [25], all the constructs in the model should have an influence in the intention to use. We should expect that habit, facilitating conditions, and intention to use should influence the effective usage of a particular technology. All moderators with the exception of price value were used according to UTAUT2 [24, 25].

Performance expectancy (PU from TAM [26]) is defined as the perceived benefits that an individual obtains by using a technology in a certain activity, and it is considered to be a good predictor of behavioural intention [24].When applied to e-health environments it has also proved to be a good predictor of behavioural intention, which indicates that patients who consider that EHR portals are useful and provide important and meaningful information are more receptive to EHR portal adoption [18, 20].

H1: Performance expectancy (PE) will positively influence behavioural intention. Age and gender will moderate the effect of PE on behavioural intention, such that the effect will be stronger amongst younger men [24, 25].

Effort expectancy (PEOU from TAM [26]) is associated with how easy it seems to be to use a certain technology [24]. Earlier research has already pointed out the usability of e-health (i.e. how easy and simple it is to use an EHR portal) as an important variable [18, 27], suggesting that patients tend to adopt EHR portals technologies more if they find the technology easy to use.

H2: Effort expectancy (EE) will positively influence behavioural intention. Age and gender will moderate the effect of EE on behavioural intention, such that the effect will be stronger amongst younger women [24, 25].

Social influence is the extent to which consumers perceive that others who are important to them, believe they should use a technology [24]. In the case of e-health there are many communities of peer-support and online forums that can influence consumers' behaviour in their decision to use or not to use EHR portals technologies. These communities allow sharing of experiences and opinions of persons with similar health conditions and in similar situations [20, 28].

H3: Social influence (SI) will positively influence behavioural intention. Age and gender will moderate the effect of SI on behavioural intention, such that the effect will be stronger amongst older women [24, 25].

Facilitating conditions is defined as the individual perception of the support available in order to use a technology [24]. One of the barriers to consumers' use of health services over the internet is the consumers' resources to access these platforms [27], suggesting that users with better conditions to use e-health technologies favour EHR portals adoption.

H4(a): Facilitating conditions (FC) will positively influence behavioural intention. Age and gender will moderate the effect of FC on behavioural intention, such that the effect will be stronger amongst older women [25].
H4(b): Facilitating conditions (FC) will have a significant influence on use behaviour. Age will moderate the effect of FC on technology use, such that the effect will be stronger amongst older people [24].

Hedonic motivation or perceived enjoyment is defined as the intrinsic motivation of an individual to obtain fun or pleasure from using a technology [25]. Hedonic motivation is considered to be a strong predictor of behavioural intention [25]. Earlier research has found that this construct is also important to e-health consumers and that it could even be a sufficient reason for adoption [29].

H5: Hedonic motivation (HM) will positively influence behavioural intention. Age and gender will moderate the effect of HM on behavioural intention, such that the effect will be stronger amongst younger men [25].

In UTAUT2 price value is defined as the perceived benefits of using a technology given its costs [25]. Even though the cost and time savings may influence individuals [30], the target technology of our study is EHR portals, and most hospitals or health institutions have free internet health services, so the price value may not be significant in behavioural intention [8, 28]

H6: Price value (PV) will have no influence on behavioural intention.

The last construct from UTAUT2 is habit. This construct refers to the automatic nature of a behaviour response resulting from learning [25]. Habit has proved to be a good predictor of different technologies' adoption, since it is a result of prior experiences [25]. We therefore test it in EHR portals adoption as well.

H7(a): Habit (HT) will positively influence behavioural intention. Age and gender will moderate the effect of HT on behavioural intention, such that the effect will be stronger for older men.[25]

H7(b): Habit (HT) will positively influence technology use. Age and gender will moderate the effect of HT on technology use, such that the effect will be stronger for older men [25].

The role of intention as a predictor of usage is critical and has been well-established not only in IS in general but also in healthcare and e-health, with the literature suggesting that the driver of using specific e-health platforms is preceded by the intention to use them [18, 21, 24, 25, 30, 31].

H8: Behavioural intention (BI) will have a significant and positive influence on technology use[24, 25].

Measurement

All of the items were adopted from Venkatesh et al. [25], Wilson and Lankton [18], and Martins et al. [32], with small modifications in order to adjust to EHR portals technology. The items are shown in Appendix 1. The questionnaire was administered in Portuguese through a web hosting service (Survey Monkey) after being translated by a professional bi-lingual translator fluent in both languages, familiar with the questionnaire terminology. In order to ensure that the content did not lose its original meaning, a back-translation was made from the Portuguese instrument to English, again by another bi-lingual professional translator fluent in both languages that had no knowledge of the questionnaire, and compared to the original [33, 34].

The scales' items were measured on a seven-point Likert type scale, ranging from "strongly disagree" (1) to "strongly agree" (7). Use was measured on a different scale. The scale from UTAUT2 (from "never" to "many times per day") was adapted to "never" to "every time I need", since EHR portals usage is not as regular as mobile internet usage. Demographic questions about age and gender were also included; age was measured in years and gender was coded as a dummy variable (0 or 1), women represented by 0.

Before the respondents could see any of the questions an introduction was made explaining the concept of EHR portals (Appendix 1). The aim of this introduction was to ensure that respondents were aware of this concept, and had prior knowledge and contact with EHR portals, because the absence of this prior knowledge is an exclusion criterion.

Data collection

To test the instrument a pilot survey was conducted in June 2013 to validate the questions and scale of the survey. From the pilot survey we had 31 responses, demonstrating that all of the items were reliable and valid. The data from the pilot survey were not included in the main survey. NOVA IMS approved and verified the ethical compliance of the questionnaire before its use. All participants were informed by email about the study purpose, confidentiality protection, anonymity of the information collected, and that by clicking on the hyperlink they would authorize their use for academic purposes.

According to the literature, the technology that we are studying (EHR portals) is being used by fewer than 7% of the total health care consumers or patients [10, 11, 35]. We are therefore sampling a group of people that could be defined as a rare population (constitutes a small proportion of the total population) and specific sample strategies can be used that are suitable for this type of research [36, 37]. The literature also reports that the users of EHR portals have higher education than the population average [30, 38, 39]. A meta-analysis pointed out that the patient factor with the greatest potential impact on the acceptance of consumer health technology was higher education [30]. Since the rate of adoption is still low in the use of EHR

portals the studies that addressed the topic under the scope of the diffusion theory also identified early adopters of EHR portals as having higher education than the average [30, 40]. As a result, we focused our sampling strategy on places where our target population (users of EHR portals) is more prevalent [36, 37], and therefore selected educational institutions.
An email was sent in September of 2013 with the hyperlink to the survey to a total of 1223 people at three institutions that provide education services, NOVA IMS, Lisbon School of Economics and Management, and Polytechnic Institute of Santarém, from which we obtained 363 responses. A reminder was sent two weeks after the first email, only to those who had not responded to the first email, in order to improve the response rate. Following the reminder, we had a total of 505 respondents (41% response rate). According to our statistical modelling we cannot use incomplete questionnaires [41, 42] and we obtained 386 questionnaires without missing data. Recent literature provides guidance about dealing with missing data in partial least squares structural equation modelling (PLS-SEM) [43]. When a construct with missing data exceeds 15% in at least 50% of its items, the cases with missing data should be excluded from the file [43, 44]. In our survey we had two constructs with more than 19% of missing data in at least 50% of their items. We also performed an evaluation regarding sociodemographic characteristics between the responses with missing data and without missing data [41, 43], identified as being relevant by the literature to the study topic [30, 38, 39]. We used the Chi-Square test to compare, gender (χ^2= 0.195; p= 0.659), age (χ^2= 0.693; p= 0.707), chronic illness status (χ^2= 0.474; p= 0.491) and education (χ^2= 2.885; p= 0.236), and no statistically significant difference was found between the groups. According to these findings the best option was to perform the listwise deletion [43, 44] and use the 386 questionnaires without missing data.

Data analysis

To test the research model we used the partial least squares (PLS), which is a causal modelling approach (i.e., a variance-based path modelling technique) [45]. The complexity of the model (i.e., many moderators), the ability of using the PLS method as theory-building method, and the fact that the PLS method is oriented to explain variance of the research model were the main reasons for choosing this method [41]. In addition, PLS was applied in both UTAUT and UTAUT2 models [24, 25]. We used SmartPLS 2.0.M3 [46], a software to estimate the PLS. Before testing the structural model we examined the measurement model to assess construct reliability, indicator reliability, convergent validity, and discriminant validity.

RESULTS

Sample characteristics

Our sample characteristics are shown in Table 2.

Table 2 - Sample characteristics (n=386)

Variable	**Category**	**Frequency (%)**
Age	18-23	149 (38.6)
	24-30	91 (23.6)
	>31	146 (37.8)
Gender	Male	147 (38.1)
	Female	239 (61.9)
Chronic Illness	No	328 (85)
	Yes	58 (15)
Education	Undergraduate	141 (36.5)
	Bachelor's degree and post-graduate	174 (45.1)
	Master Degree or more	71 (18.4)

Measurement model

The results of the measurement model are shown in Tables 3, 4, and 5. To evaluate construct reliability, one can use the Cronbach's alpha (CA) or the composite reliability coefficient (CR). The most common measure to estimate the internal consistency reliability of the measures is CA, which assumes that all indicators of a construct are equally reliable [41]. Although CA is more often used, CR is more appropriate for PLS, since it prioritizes indicators according to their individual reliability and also takes into account that indicators have different loadings, unlike CA. Table 3 reports that all constructs have both CA and CR greater than 0.70, showing evidence of internal consistency [47].

Table 3 - Descriptive statistics, Cronbach's alpha, and composite reliability

Construct	Mean	SD	Cronbach's alpha	Composite reliability (CR)	Average variance extracted (AVE)
Performance Expectancy	5.30	1.33	0.90	0.94	0.83
Effort Expectancy	5.53	1.09	0.91	0.94	0.77
Social Influence	2.97	1.62	0.97	0.98	0.96
Facilitating Conditions	5.76	1.19	0.81	0.88	0.64
Hedonic Motivation	4.48	1.53	0.93	0.96	0.88
Price Value	4.32	1.39	0.94	0.96	0.88
Habit	3.07	1.38	0.73	0.85	0.66
Behaviour Intention	4.87	1.34	0.91	0.94	0.64

In order to have good indicator reliability it is desired that the latent variable explains more than half of the indicators' variance. The correlation between the constructs and their indicators should thus be greater than 0.7 ($\sqrt{0.5} \approx 0.7$) [41, 43, 47] . However, it is recommended to eliminate an item only if its outer standardized loadings are lower than 0.4 [43, 48]. The measurement model has no issues with the indicators' reliability; FC4 is the only construct lower than 0.7, but it is still greater than 0.4 [43] (Table 4).

Table 4 - PLS loadings and cross-loadings

Construct	Item	PE	EE	SI	FC	HM	PV	HT	BI
Performance expectancy	PE1	**0.86**	0.39	0.19	0.17	0.39	0.27	0.30	0.37
	PE2	**0.95**	0.45	0.31	0.25	0.47	0.30	0.42	0.51
	PE3	**0.93**	0.45	0.36	0.23	0.45	0.33	0.45	0.49
Effort expectancy	EE1	0.36	**0.87**	0.16	0.52	0.32	0.26	0.20	0.37
	EE2	0.48	**0.92**	0.26	0.51	0.44	0.33	0.29	0.42
	EE3	0.42	**0.86**	0.26	0.49	0.44	0.34	0.30	0.36
	EE4	0.43	**0.91**	0.21	0.53	0.37	0.29	0.28	0.41
Social influence	SI1	0.31	0.25	**0.97**	0.22	0.26	0.34	0.56	0.43
	SI2	0.31	0.23	**0.98**	0.20	0.30	0.34	0.55	0.43
	SI3	0.31	0.25	**0.98**	0.22	0.32	0.34	0.56	0.45
Facilitating conditions	FC1	0.16	0.43	0.10	**0.82**	0.17	0.17	0.16	0.22
	FC2	0.20	0.51	0.20	**0.90**	0.24	0.25	0.21	0.26
	FC3	0.26	0.54	0.14	**0.84**	0.28	0.18	0.18	0.29
	FC4	0.14	0.34	0.28	**0.63**	0.32	0.27	0.28	0.18
Hedonic motivation	HM1	0.44	0.36	0.29	0.25	**0.96**	0.41	0.45	0.40
	HM2	0.49	0.50	0.28	0.38	**0.91**	0.37	0.43	0.41
	HM3	0.42	0.38	0.29	0.24	**0.96**	0.41	0.44	0.40
Price value	PV1	0.23	0.28	0.28	0.22	0.33	**0.91**	0.38	0.31
	PV2	0.35	0.35	0.34	0.28	0.43	**0.96**	0.46	0.36
	PV3	0.34	0.33	0.35	0.25	0.41	**0.95**	0.47	0.37
Habit	HT1	0.31	0.24	0.59	0.24	0.33	0.43	**0.88**	0.53
	HT2	0.25	0.13	0.44	0.14	0.39	0.36	**0.80**	0.40
	HT3	0.50	0.34	0.33	0.21	0.44	0.33	**0.74**	0.54
Behaviour intention	BI1	0.54	0.48	0.36	0.33	0.45	0.34	0.57	**0.90**
	BI2	0.44	0.39	0.41	0.25	0.38	0.32	0.54	**0.94**
	BI3	0.41	0.34	0.45	0.24	0.36	0.36	0.57	**0.91**

In order to assess the convergent validity we used average variance extracted (AVE). The AVE should be greater than 0.50, so that the latent variable explains, on average, more than 50% of its own indicators [49]. As shown in Table 3, none of the constructs have the AVEs lower than 0.64, so all of the indicators satisfy this criterion.

Finally, discriminant validity can be evaluated with the Fornell-Larcker criterion [49]. This criterion claims that a latent variable shares more variance with its indicators than with the other latent variables, so that the square root of AVEs should be greater than the correlations between the construct [41, 49]. As seen in Table 5, all diagonal elements (square root of AVEs) are greater than the correlations between constructs (off diagonal elements). In addition, another criterion can be assessed, although it is a more liberal one [41]. We also examined each construct to ascertain that its loadings are greater than all of its cross-loadings [42, 50]. This criterion is also met, as seen in Table 4.

Table 5 – Correlations and square root of AVEs

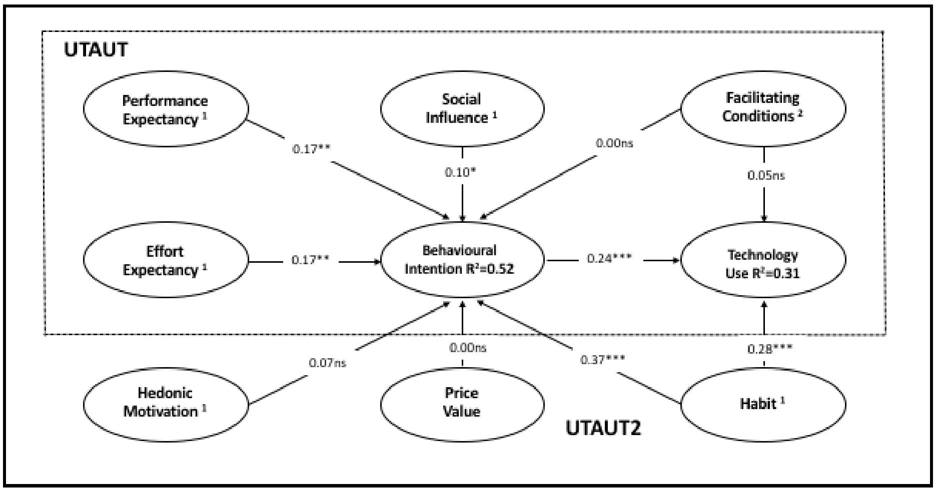
	PE	EE	SI	FC	HM	PV	HT	BI	Gender	Age	Use
PE	**0.91**										
EE	0.47***	**0.88**									
SI	0.32***	0.25***	**0.98**								
FC	0.24***	0.57***	0.22***	**0.80**							
HM	0.48***	0.44***	0.31***	0.31***	**0.94**						
PV	0.33***	0.34***	0.35***	0.27***	0.42***	**0.94**					
HT	0.44***	0.29***	0.57***	0.25***	0.47***	0.47***	**0.81**				
BI	0.53***	0.44***	0.38***	0.34***	0.47***	0.33***	0.58***	**0.80**			
Gender	-0.01	-0.05	0.05	-0.01	-0.06	0.06	-0.01	-0.04	N.A.		
Age	0.00	-0.05	0.12*	-0.02	-0.03	0.06	0.10	0.04	-0.12*	N.A.	
Use	0.25***	0.20***	0.43***	0.22***	0.16**	0.25***	0.42	0.01	0.23***	0.50***	N.A.

Notes:
1. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; FC: Facilitating conditions; HM: Hedonic motivation; PV: Price value; BI: Behavioural intention; Gender: Gender; Age: Age; HT: Habit.
2. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$
3. Diagonal elements are square roots of AVEs
4. Off-diagonal elements are correlations.

In sum, all assessments are satisfactory. This means that the constructs can be used to test the conceptual model.

Structural model

The structural model was run in two separate models: direct effects only (D), and direct and moderated effects (D+I). The path significance levels were estimated using a bootstrap with 500 iterations of resampling. Figure 2 shows the path coefficients, their significance levels, and R^2. For a better understanding and reading of the figure, we do not show the path model of the moderators (age and gender). The R^2 was used to evaluate the structural model. Overall, the model explains 52% and 31% of the variance in behavioural intention and technology use, respectively.



Notes: ***p <0.001; **p<0.01; *p<0.05; ns: non-significant;
1. Moderated by age and gender;
2. Effect on behavioural intention is moderated by age and gender; effect on technology use is moderated by age.

Figure 2 - Structural model results

As Table 6 (D+I) shows, the predictors of behavioural intention are performance expectancy ($\hat{\beta}$=0.17; p<0.01), effort expectancy ($\hat{\beta}$=0.17; p<0.01), social influence ($\hat{\beta}$=0.10; p<0.05), and habit ($\hat{\beta}$=0.37; p<0.001). These constructs partially support hypotheses H1, H2, and H3, since age and gender have no significant influence while moderating the effect of each construct on behavioural intention. H7(a) is fully supported, as age and gender do moderate the influence of habit on intention ($\hat{\beta}$=0.12; p<0.05), which means that it is more important for older men. Price value ($\hat{\beta}$=0.00; p>0.05) proved to be non-significant. This means that price value has no influence on behavioural intention, therefore supporting H6. On the other hand, facilitating conditions ($\hat{\beta}$=0.00; p>0.05) and hedonic motivation ($\hat{\beta}$=0.07; p>0.05) are non-significant in predicting behavioural intention. Hence, hypotheses H4(a) and H5 are not supported.

We found that habit is positive and statistically significant ($\hat{\beta}$=0.28; p<0.001) as a predictor of technology use. However, age and gender do not moderate the influence of habit on use ($\hat{\beta}$=0.01; p>0.05), and therefore H7(b) is only partially supported. Behavioural intention also has a significant and positive influence on technology use ($\hat{\beta}$=0.24; p<0.001). Hypothesis H8 is supported. Age also has a positive and significant effect on technology use. This finding suggests that older individuals use EHR portals technologies more than younger individuals do. Facilitating conditions is the only construct having no statistically significant impact on use ($\hat{\beta}$=0.05; p>0.05), and for that reason H4(b) is not supported.

Table 6 - Structural model results

	Behavioural intention		Technology use	
	D only	D+I	D only	D+I
R^2	0.48	0.52	0.26	0.31
Adj. R^2	0.47	0.51	0.25	0.30
Performance expectancy (PE)	0.20***	0.17**	--	--
Effort expectancy (EE)	0.18**	0.17**	--	--
Social influence (SI)	0.10*	0.10*	--	--
Facilitating conditions (FC)	0.02	0.00	0.05	0.05
Hedonic motivation (HM)	0.03	0.07	--	--
Price value (PV)	0.01	0.00	--	--
Habit (HT)	0.39***	0.37***	0.32***	0.28***
Behavioural intention (BI)	--	--	0.23***	0.24***
Age	--	0.04	--	0.17***
Gender	--	-0.03	--	-0.06
Gender x Age	--	-0.03	--	--
PE x Age	--	-0.02	--	--
PE x Gender	--	0.03	--	--
PE x Gender x Age	--	-0.05	--	--
EE x Age	--	-0.01	--	--
EE x Gender	--	-0.04	--	--
EE x Gender x Age	--	0.00	--	--
SI x Age	--	-0.03	--	--
SI x Gender	--	-0.06	--	--
SI x Gender x Age	--	-0.05	--	--
FC x Age	--	0.02	--	0.04
FC x Gender	--	-0.07	--	--
FC x Gender x Age	--	0.03	--	--
HM x Age	--	-0.09	--	--
HM x Gender	--	-0.10	--	--
HM x Gender x Age	--	-0.08	--	--
PV x Age	--	0.09*	--	--
PV x Gender	--	0.01	--	--
PV x Gender x Age	--	0.05	--	--
HT x Age	--	0.03	--	-0.12*
HT x Gender	--	0.08	--	0.03
HT x Gender x Age	--	0.12*	--	0.01

Notes:
1. D only: Direct effects only; D+I: Direct and moderated effects
2. *** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$

DISCUSSION

Our study has sought to apply the extended unified theory of acceptance and usage technology – UTAUT2 [25] – to the special case of patients' EHR portals acceptance, in order to determine if the constructs proposed in this model help to explain behavioural intention and technology use of EHR portals.

Theoretical implications

Our results suggest that using UTAUT2 in a health related area yields good results, explaining 52% of the variance in behavioural intention and 31% of the variance in technology use. The most important contributors are performance expectancy, effort expectancy, social influence, and habit.

Table 7 presents a summary of all the hypotheses tested and their support (or not) based on statistical tests. Overall, most of our hypotheses were supported or partially supported. In most cases age and gender did not moderate the effects of the constructs on the dependent variables, except for the effect of habit (which is moderated by age and gender) and price value (which is moderated by age) on behavioural intention; and habit (which is moderated by age) on technology use. The rejection of the facilitating conditions' hypotheses suggests that the subjects in our sample consider that the resources or knowledge to use EHR portals are not an issue. This can be explained by the facility of having access to a computer and to the internet. In 2013 62% of Portuguese individuals between 16 and 74 years of age had access to internet in their households [51], and almost every individual (95%) had access to the internet in their workplace in 2011 [3, 52]. Hedonic motivation also has no significant importance on behavioural intention.

On the other hand, our subjects give importance to the simplicity of the EHR portals, suggesting that individuals care about the result (performance expectancy) and the necessary effort (effort expectancy) it takes to use the system. When it comes to price value, it did not have a significant impact on the intention of our respondents, but when price value is moderated by age, this effect is significant, specifically when age increases. It seems that older individuals, who usually are likely to have more health problems, attribute greater value to the benefits of EHR portals [53]. Social influence is also an important variable in the intention to use EHR portals. Individuals are apparently influenced by important people in their lives to use an EHR portal. The study's results also point out that those individuals who already have the habit of using EHR portals are more likely to use them. The same applies to behavioural intention effect on use, which indicates that subjects who have the intention to use EHR portals will be more likely to actually use them.

Habit, one of the new constructs coming from UTAUT2 [25], proved to have the most significant effect on behavioural intention and on technology use as well. This specific construct, which was shown to be the most important in explaining the adoption of EHR portals, was not tested in the studies that were identified addressing similar topics [1, 18-20, 22, 23], showing the importance of using UTAUT2 to understand the factors that drive individuals to adopt EHR portals. The demographic characteristics of our sample deviate from the population average insofar as they comprise persons who are younger and persons who have higher education, which is in line with the findings of earlier studies [30, 38, 39].

Table 7 – Summary of findings regarding Hypotheses

Path	Beta	t-value	Hypotheses	Result
PE → BI	0.17	3.15**	H1	Partially supported
PE x Gender x Age → BI	-0.05	0.80ns		
EE → BI	0.17	2.67**	H2	Partially supported
EE x Gender x Age → BI	0.00	0.04ns		
SI → BI	0.10	1.97*	H3	Partially supported
SI x Gender x Age → BI	-0.05	0.94ns		
FC → BI	0.00	0.00ns	H4(a)	Not supported
FC x Gender x Age → BI	0.03	0.46ns		
FC → UB	0.05	1.14ns	H4(b)	Not supported
FC x Age → UB	0.04	0.83ns		
HM → BI	0.07	1.44ns	H5	Not supported
HM x Gender x Age → BI	-0.08	1.24ns		
PV → BI	0.00	0.07ns	H6	Supported
HT → BI	0.37	6.54***	H7(a)	Supported
HT x Gender x Age → BI	0.12	1.98*		
HT → UB	0.28	4.67***	H7(b)	Partially supported
HT x Gender x Age → UB	0.01	0.20ns		
BI	0.24	3.90***	H8	Supported

Notes:
1. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; FC: Facilitating conditions; HM: Hedonic motivation; PV: Price value; BI: Behavioural intention; Gender: Gender; Age: Age; HT: Habit.
2. *** p < 0.001; ** p < 0.01; * p < 0.05; ns = non-significant

Managerial implications

The findings of this study should generate important managerial implications for the conceptualization, design, and implementation of an EHR portal system. We found in our study that performance expectancy and effort expectancy have a significant impact on the adoption of EHR portals. Earlier studies using TAM also identified these constructs as being important for the adoption of Patient Portals [18, 19]. A very recent study using a TAM extension also found performance expectancy and effort expectancy in the adoption of patient focus e-health technologies to be important [22]. One study adopted a qualitative TAM approach to evaluate Patient Portals [19], and the opinion of healthcare consumers in this study was that the design of these platforms should be simple and easy to use [19]. A recent qualitative study that specifically addressed the reasons why the voluntary uptake and use of EHRs have been low [5], mentioned that the patients wanted a unified view of their medical issues and health management tools [3, 5, 54]. In fact, they want an easier and more effective manner to access their information [5] which is aligned with our study findings that performance expectancy and effort expectancy are important for the patients. It is very important when designing or redeploying an EHR portal to make it easy and simple to use, and we therefore suggest that a pilot application should be tested by the potential users of the platform so that improvements can be made in the development stage to increase the acceptance of the platform [55, 56]. Social influence is also an important variable in the intention to use EHR portals, as demonstrated by the results of our study. Because this influence may come from online support groups, as reported in other studies [20, 35], digital strategies to promote e-health tools by using social networks (e.g. Facebook) should be useful in promoting the adoption and use of EHR portals. A study of a failed implementation of this type of technology identified insufficient or incorrect promotion as one of the possible reasons for failure [35]. This finding was complement by a more recent study reporting that lack of awareness and knowledge about the EHR portals was patients' greatest barrier to use them [5]. It was hypothesized in another recent study that the cost of e-health technologies could influence their adoption by older people, and UTAUT2 might be a good model to test this [53]. Also, another recent study suggested that one the reasons for failure within EHR portals was the fee charged to the patient to access their account [35]. Our study showed that as age increases the cost of accessing EHR portals is important for the patient, so our suggestion to hospitals, clinics, and governmental institutions is to maintain free access to these EHR portals in order to avoid acceptance problems, as in other previous implementations [35, 53].

Our results suggest that there is a significant impact of healthcare consumers' habit on EHR portals use. In addition to the direct and automatic effect of habit on technology use, habit also operates as a stored intention path to influence behaviour. This demands more marketing communication efforts to strengthen both the stored intention and its link to behaviour. It was also mentioned in the literature as relevant the lack of training provided to the patients by the healthcare providers regarding the use of EHR and Patient Portals [5]. In our study the construct facilitating conditions which is linked to the resources available to use EHR portals, was not statistically significant, but habit was significant, and habit is linked to repeated usage that can be promoted when the resources available promote continuous usage, such as on-line training tools and technical support services [25] . The evaluation of the results of our model in a managerial perspective together with the findings of earlier studies gives an added value with new insights for management decisions concerning the creation of EHR portals.

Limitations and future research

The study has limitations. We acknowledge that this research is limited by the geographic location, as it pertains to one country only and education institutions. According to the literature, the technology that we are studying – EHR portals – is being used by fewer than 7% of the total health care consumers or patients [10, 11, 35]. According to the literature, users and early adopters of these types of platforms are younger than the population average and have significantly higher education [30, 38, 39]. Using a sampling strategy suitable to low prevalence populations [36, 37], we focused our sampling on education institutions, where our target population is more concentrated [41, 42, 45]. It is also common to find studies that evaluate e-health portals addressing the users of a particular portal [18, 23, 30]. This is also a good strategy to target rare populations, but is also potentially biased, as it reflects the opinion of only the users of a certain portal [41, 42, 45].

Regarding the model tested (UTAUT2), it has no health related construct. We suggest that future research include and test patients' personal empowerment variables associated with technology acceptance and use in order to improve the explained variance of behavioural intention and use of EHR portals [20]. It could be very interesting in future research to use UTAUT2 with a qualitative approach. Some researchers in this field have already used adoption models in e-health services with a qualitative approach in the case of both health care professionals [57] and patients [19], but not with UTAUT2. Furthermore, and also regarding UTAUT2, the experience moderator could bring more explanatory power to the model, since habit has a major impact on the dependent variables. Future research should therefore also collect experience information, at least in a self-reported way. It could also be interesting in future studies to compare the results of these predictions with actual features use of EHR portals. This could be done in a between-countries cooperative setting in which EHR portals have been successfully implemented. Finally, another very interesting and up-to-date research topic would be e-health applied to mobile phones, that is, m-health. Although there are some studies in this field [58-60], applying UTAUT2 might yield results of great interest.

CONCLUSION

EHR portals adoption is a new and growing field of study that is an important topic in government-level discussions in the EU and the US. This research has consequently sought to understand the acceptance by patients of EHR portals technology. For that, we used a new model proposed by Venkatesh et al. [25] – UTAUT2 – that has a well-tested basis of technology acceptance constructs combined with more consumer centred variables. The research model was tested in a Portuguese context and found to explain 52% of the variance in behavioural intention and 31% of the variance in EHR portals technology use. Of all the constructs tested, performance expectancy, effort expectancy, social influence, and habit had the most significant effect over behavioural intention. Habit is more important for older men, as is price value for older individuals on behaviour intention. Habit and behavioural intention had the most significant effect over technology use; age is also a facilitator to explain technology use, older individuals tend to use it more, probably because health concerns and problems increase with age [53] and habit is attenuated by age. It seems that habit is more important for younger individuals in explaining technology use. Furthermore, facilitating conditions and hedonic motivation had no significant impact on EHR portals adoption. Price value also did not influence adoption, as we hypothesized, except when moderated by age.

Our findings strongly suggest that by using the consumer adoption specific constructs, we achieve a better understanding of the adoption of EHR portals. Our study helped to understand the technology side of EHR portals adoption. Further research should combine technology with health drivers, and with more evidence-based theory, in order to improve the knowledge in this field of study.

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