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Electronic Health Record Portals Adoption by Health Care Consumers

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To Constança and Letícia.

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ABSTRACT

Electronic Health Record (EHR) portals, also called EHR patient portals, have received great attention and investment at the government level worldwide, like the multi-billion dollar US initiative, named meaningful use program. According to the literature review, there is still a lack of studies that address the topic of understanding why people adopt and use EHR Portals, making this a field of knowledge that requires more research. According to the findings in the literature review the complexity of EHR portals requires having a patient-centred model that should be able to cover additional dimensions related with health behaviour, confidentiality concerns, and innovation drivers. Potential adoption differences between countries with different regulations in their health care systems should also be tested. With this dissertation, we contribute to a better understanding of the factors that lead health care consumers to use and adopt EHR portals. To this end we develop four empirical studies.

In the first empirical study (Chapter 3) we tested the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) in Portugal. Being a consumer- centred model, it was important to evaluate its feasibility to study the EHR portals adoption determinants by the health care consumers. Several constructs in the model helped explain the adoption of EHR portals: performance expectancy, effort expectancy, social influence and habit. With habit a consumer specific construct from UTAUT2 having the most relevant impact in both behavioural intention and use. UTAUT2 showed its importance as a consumer-focused model identifying the factors that drive health care consumers to use EHR portals.

In the second empirical study (Chapter 4) -also tested in Portugal- we extended the UTAUT2 model by adding a health specific construct, self-perception. This construct showed its relevance by being a statistically significant predictor of behavioural intention, demonstrating the usefulness of including a construct derived from the Health Belief Model (HBM), in a technology applied in the field of health care.

In the third empirical study (Chapter 5) we performed a cross-country analysis between US and Portugal combining UTAUT2 with the Concern for Information Privacy (CFIP) framework. We made an assessment of the potential differences between the determinants of adoption between the two countries with different health care regulations and health care models. In the US there is no national health system (NHS) coverage and the patients need to have an expensive private insurance or pay directly to the health care provider to have health care support, while in Portugal

there is universal health coverage. It was hypothesized and confirmed via the price value construct that the value that the US health care consumers give to a tool like EHR portals is statistically significantly greater than the Portuguese health care consumers. It was also expected that confidentiality concerns in US are greater than in Portugal, due to the less strict regulation in US regarding patient data confidentiality. This was measured by the CFIP framework, but confidentiality concerns were not an issue in either US or Portugal. Social influence, hedonic motivation, and price value were predictors only in the US group. With this study we verified the importance to perform cross-country evaluations when studying EHR portals adoption.

In the fourth empirical study (Chapter 6) we used the evidence from the previous empirical studies plus the literature review to propose a new research model that integrates constructs from UTAUT2, HBM, and the Diffusion of Innovation (DOI) theory. In this study, we performed a national survey based on randomly generated mobile phone numbers, when in the previous empirical research, we targeted our sample to educational institutions. We used a two-phase sampling approach. In the first phase, we asked potential respondents if they were users of EHR portals and if yes, if she/he was interested in replying to our main survey (second phase). From this sample regarding the question to identify the users of EHR portals, we obtained 8.6% EHR portals usage in the adult Portuguese population. A relevant contribution from our study to understand the usage of this type of technology at country level. All three theories contributed with constructs that help to understand EHR portals adoption. The final research model obtained the best results from the all of the empirical studies executed in this dissertation with 76.0% of variance explained in behavioural intention and 61.8% of variance explained in use behaviour.

In this dissertation's conclusions (Chapter 7), we provide more detailed insights about the overall contributions of this dissertation, managerial implications to develop and implement better EHR portals, limitations and avenues for future research about EHR portals.

Keywords: DOI; eHealth; health care consumers; EHR; EHR portals; HBM; patients; UTAUT2; technology adoption

RESUMO

Os Portais de Registo de Saúde Eletrónicos (PRSE), também denominados portais do doente, têm recebido bastante atenção e investimentos a nível governamental em todo o Mundo, tendo como exemplo a iniciativa multibilionária *"meaningful use program"* nos Estados Unidos da América. De acordo com a revisão da literatura, ainda existe uma lacuna no estudo das razões pelas quais as pessoas adotam e usam os PRSE, fazendo desta uma área de conhecimento que necessita de mais investigação. De acordo com a revisão da literatura, a complexidade dos PRSE, requere um modelo centrado no doente e que seja capaz de cobrir dimensões adicionais relacionadas com o comportamento na saúde, preocupações de confidencialidade e inovação. Potenciais diferenças na adoção entre países com diferentes regulamentações nos sistemas de saúde também deverão ser testadas. Com esta dissertação procuramos contribuir para um melhor conhecimento dos fatores que levam os consumidores na saúde a usar e adotar PRSE. Com este propósito desenvolvemos quatro estudos empíricos.

No primeiro estudo empírico (Capítulo 3), testamos em Portugal o modelo de *"Extended Unified Theory of Acceptance and Use of Technology"* (UTAUT2). Sendo um modelo centrado no consumidor, era importante avaliar a sua adequação para estudar os determinantes de adoção dos PRSE pelos consumidores na saúde. Vários fatores no modelo ajudaram a explicar a adoção dos PRSE: expectativa de desempenho, expectativa de esforço, influência social e hábito. Sendo o hábito um fator especifico da área do consumidor do UTAUT2, demonstrou este fator o impacto mais relevante tanto na intenção de uso como no uso efetivo. O UTAUT2 demonstrou a sua importância como um modelo centrado no consumidor, identificando os fatores que influenciam os consumidores na saúde a usarem PRSE.

No segundo estudo empírico (Capítulo 4), também testado em Portugal, estendemos o modelo de UTAUT2, adicionando um fator especifico da saúde, auto- perceção. Este fator demonstrou a sua relevância, tendo uma influência estatisticamente significativa sobre a intenção de uso, demonstrando a utilidade de incluir um fator derivado do *"Health Belief Model"*(HBM), numa tecnologia aplicada à saúde.

No terceiro estudo empírico (Capítulo 5), executamos uma análise entre os Estados Unidos da América e Portugal combinando o UTAUT2 e o *"Concern For Information Privacy"* (CFIP). Foi feita uma avaliação das potenciais diferenças entre os dois países, com diferentes regulamentações e modelos de saúde, no que diz respeito aos determinantes de adoção. Nos

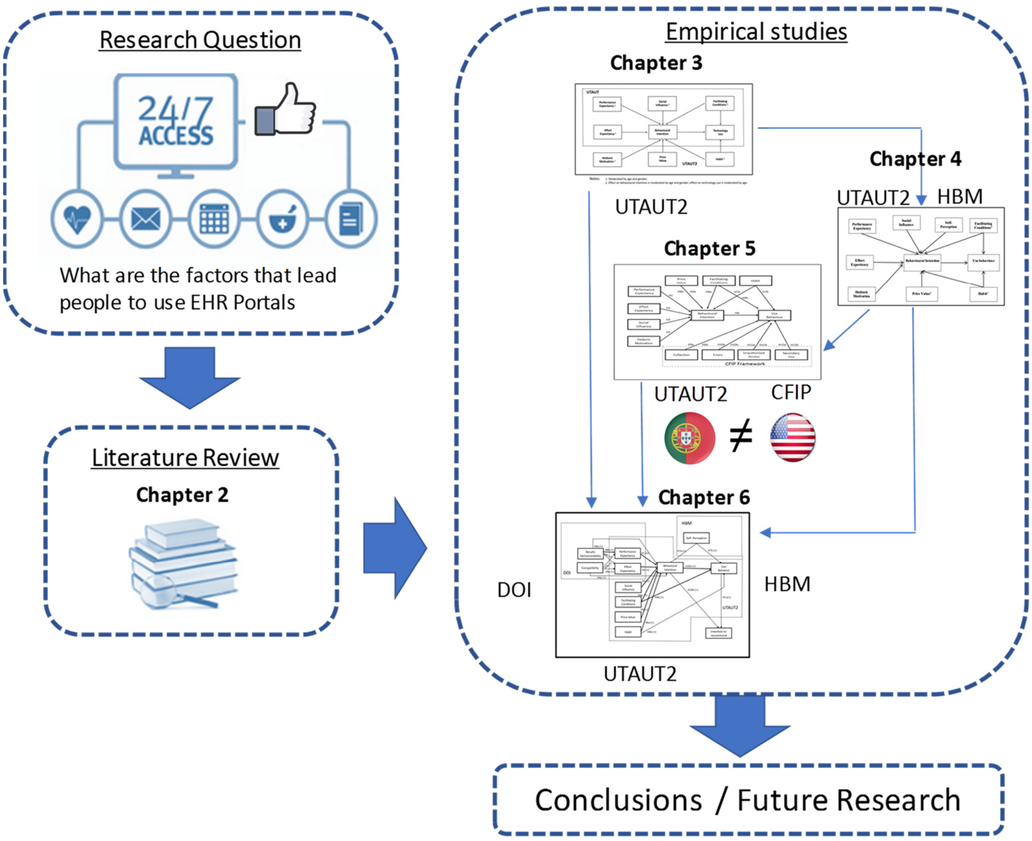
Estados Unidos não existe um sistema nacional de saúde e os doentes têm de ter um seguro privado de saúde bastante dispendioso ou pagarem diretamente as suas despesas ao prestador dos cuidados de saúde, por sua vez em Portugal existe uma cobertura universal dos cuidados de saúde. Foi testada e confirmada a hipótese através do fator preço-valor, que nos Estados Unidos da América, o valor que os consumidores na saúde dão aos PRSE é maior do que em Portugal, sendo esta diferença estatisticamente significativa. Também seria esperado que as preocupações com a confidencialidade fossem maiores nos Estados Unidos da América do que em Portugal, devido a uma regulamentação menos restritiva nos Estados Unidos da América relativamente à confidencialidade dos dados clínicos dos doentes. Utilizamos o CFIP para este propósito, no entanto as preocupações relativamente à confidencialidade, não demonstraram ser um problema tanto nos Estados Unidos da América como em Portugal. A influência social, motivação hedónica e preço-valor, foram fatores relevantes apenas nos Estados Unidos da América. Com este estudo, verificamos que é importante fazer comparações entre países para estudar a adoção de PRSE.

No quarto estudo empírico (Capítulo 6), utilizamos a evidência dos estudos empíricos anteriores e da revisão da literatura para propor um novo modelo que integra fatores do UTAUT2, HBM e *"Diffusion of Innovation"* (DOI). Neste estudo foi feita uma sondagem nacional, utilizando uma amostra aleatória de números de telemóvel, enquanto que nos estudos empíricos anteriores, utilizamos amostras obtidas em instituições com fins educacionais. No processo de amostragem utilizamos duas fases. Na primeira fase perguntamos aos inquiridos se eram utilizadores de PRSE e só depois se a reposta fosse afirmativa se estariam interessados em responder ao inquérito principal do estudo (segunda fase). Desta amostragem e relativamente à questão utilizada para identificar utilizadores de PRSE obtivemos 8.6% de uso na população adulta portuguesa. Uma contribuição importante do nosso estudo para o entendimento da utilização deste tipo de tecnologia ao nível de um país. As três teorias contribuíram com fatores que ajudam a compreender a adoção de PRSE. O modelo final obteve os melhores resultados de todos os estudos empíricos desta dissertação com 76.0% da variância explicada em intenção de uso e 61.8% da variância no uso.

Nas conclusões desta dissertação (Capítulo 7), é descrito em maior detalhe todas as contribuições desta dissertação, implicações para decisões de gestão relativamente ao desenvolvimento e implementação de melhores PRSE e limitações e novos caminhos de investigação a ser seguidos para os PRSE.

Palavras-chave: adoção de tecnologia; consumidores na saúde; DOI; doentes; eHealth; HBM; Portais de registo de saúde eletrónicos; registos eletrónicos de saúde; UTAUT2

GRAPHICAL ABSTRACT



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Abbreviations & Acronyms

AVE	Average Variance Extracted
BI	Behavioural Intention
CD	Chronic Disability
CFIP	Concern for Information Privacy
CL	Collection
CMS	Centers for Medicare & Medicaid Services
CMV	Common Method Variance
CO	Compatibility
CR	Composite Reliability Coefficient
DOI	Diffusion of Innovation
EE	Effort Expectancy
EHR	Electronic Health Record
ELM	Elaboration Likelihood Model
epSOS	European Patients Smart Open Services
EU	European Union
FC	Facilitating Conditions
HBM	Health Belief Model
HIT	Health Information Technology
HM	Hedonic Motivation
HT	Habit

ICT	Information Communication Technology
IR	Intention to Recommend
IS	Information Systems
IT	Information Technology
MGA	Multi-Group Analysis
NOVA IMS	Nova Information Management School
PE	Performance Expectancy
PEOU	Perceived Ease of Use
PLS	Partial Least Square
PT	Portugal
PU	Perceived Usefulness
PV	Price Value
RD	Results Demonstrability
SEM	Structural Equation Modelling
SI	Social Influence
SP	Self-Perception
SU	Secondary Use
TAM	Technology Acceptance Model
UA	Unauthorized Access
UB	Use Behaviour
US	United States
UTAUT	Unified Theory of Acceptance and Use of Technology

UTAUT2	Extended Unified Theory of Acceptance and Use of Technology (in a consumer context)
VAF	Variance Accounted for
VIF	Variance Inflation Factor

Chapter 1- Introduction

1.1 Motivation

This dissertation focuses on a specific type of eHealth technology, the electronic health records (EHR) portals, which give patients access to medical records, exam results, and services, such as appointment scheduling, notification systems, and e-mail access to their physician (Gordon & Hornbrook, 2016; Tavares & Oliveira, 2016b; Weingart, Rind, Tofias, & Sands, 2006). Understanding the acceptance and use of eHealth technology by health care consumers is a very relevant topic with clear benefits for society and future sustainability of the Health Care System (Angst & Agarwal, 2009; Or & Karsh, 2009). Warning signs indicate that the number of patients with chronic diseases is projected to grow by 45% between 2007 and 2025 and the workforce will be 10% smaller (Alpay, Henkemans, Otten, Rovekamp, & Dumay, 2010). Combining these two trends, there will be less health professionals available in the future to support patients. EHR portals may help patients carry out self-management activities making the health care system more effective and sustainable, not only from the patient care standpoint but also from the financial perspective due to the increasing cost of the health care budget in different countries (Alpay et al., 2010; Tavares & Oliveira, 2014b).

We can define an EHR Portal as a web based application that combines an EHR system and a Patient Portal (Ancker, Osorio, et al., 2015; Otte-Trojel, de Bont, van de Klundert, & Rundall, 2014). The terminology and concept are not uniform between different studies and countries. Some mention it as EHR patient portals, others as EHR portals, and even others use more IT specific terminologies such as EHR-tethered portals (Ancker, Osorio, et al., 2015; Jhamb et al., 2015; Otte-Trojel et al., 2014; Tavares & Oliveira, 2017). Mainly in the last three years significant policies across Europe and US have promoted the development of this specific technology (Bush et al., in press; Nambisan, 2017; Tavares & Oliveira, 2016b). The initial patient portals focused mainly on providing a point of access for patients to schedule their appointments with the physicians and to be a way of communication between the patients and health care providers (Otte-Trojel et al., 2014; Tavares & Oliveira, 2016b). More recently, patient portals started to incorporate the patients’ EHRs, on top of the existing features (e.g. appointment scheduling) (Otte-Trojel et al., 2014; Tavares & Oliveira, 2016b).

The most significant policy for the adoption and use of EHR, started in US in 2009 when the Congress approved the Health Information Technology for Economic and Clinical Health Act (HITECH), which provided incentive payments through Medicare and Medicaid to clinicians and hospitals when they use EHRs (Blumenthal & Tavenner, 2010). Through HITECH, the federal government committed unprecedented resources to supporting the adoption and use of EHRs. It made available incentive payments summing up to $27 billion during a period of 10 years (Blumenthal & Tavenner, 2010; Otte-Trojel et al., 2014). Equally important, HITECH's goal is not adoption alone but "meaningful use" of EHRs — that is, their use by providers to achieve significant improvements in care. Particularly relevant to the patients was the so called "stage 2 meaningful use" that started in 2014 (Nambisan, 2017). It requires that the eligible professionals and health care facilities that take part in Medicare and Medicaid EHR incentive programs must provide their patients secure online admission to their health information, including EHRs (Bush et al., in press; Nambisan, 2017). Stage 2 meaningful use increased the growth of new integrated EHR portals in the US by health care providers who, according to the new guidance, must not only implement it but also prove effective usage by the patients (Mitchell & Waldren, 2014; Nambisan, 2017; Otte-Trojel et al., 2014). In Europe a trans-European initiative, the European Patients Smart Open Services (epSOS) focused on developing a practical eHealth framework and Information and Communication Technology (ICT) infrastructure that enables secure access and share of patient health information amongst different European health care systems (epSOS, 2014). This project ended in June 2014 and included the possibility of the patients accessing their existing patient summaries generated and kept in other countries (different from the home country) with or without the presence of a health professional at the point of care (e.g. Hospital) or elsewhere (epSOS, 2014; Tavares & Oliveira, 2016b). This shows a trend in developing portals that will enable the sharing of information between the different health care providers, allowing at the same time full data access to the patient, in a true EHR Portal concept, in which the initial Patient Portal approach and the EHR system should merge, and the patient clinical data will be the core of the system (EHR Portal).

The importance of EHR portals is clearly perceived by the recent intuitional and governmental initiatives, which increased substantially the implementation of this technology in several developed countries in the world (Gheorghiu & Hagens, 2017; Tavares & Oliveira, 2016a). Thus, it is of critical importance to understand the reasons that lead health care consumers to use EHR portals.

1.2 Adoption Theories in Health Information Technologies

The most commonly used theories in health information technologies at individual level are: Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Ahadzadeh, Pahlevan Sharif, Ong, & Khong, 2015; Dunnebeil, Sunyaev, Blohm, Leimeister, & Krcmar, 2012; Ketikidis, Dimitrovski, Lazuras, & Bath, 2012; Maillet, Mathieu, & Sicotte, 2015; Vanneste, Vermeulen, & Declercq, 2013). The majority of the studies published within health information technologies have focused on the healthcare professionals, adoption and usage (Chang & Hsu, 2012; Chang, Hwang, Hung, & Li, 2007; Li, Talaei-Khoei, Seale, Ray, & MacIntyre, 2013; Yi, Jackson, Park, & Probst, 2006). This dissertation evaluates the patients' or health care consumers adoption and usage of EHR portals. For this reason we used as a starting point the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) model, because it was developed as an IT adoption theory with consumer oriented specific constructs, and extended this model with new constructs and theories that are specific to the topic we are studying (Venkatesh, Thong, & Xu, 2012). In the process of developing a new research model that helps to explain EHR portals, we tested and used other constructs and theories such as: Health Belief Model (HBM), which is a specific adoption theory from the health care environment (Jones et al., 2015), the Concern for Information Privacy (CFIP) framework, which is used to evaluate EHR adoption confidentiality concerns (Angst & Agarwal, 2009), and the Diffusion of Innovation (DOI), a very useful model to evaluate adoption when a new technology is implemented (Rogers, 2003).

1.3 Research Focus

This dissertation's focus is on understanding the drivers of EHR portals adoption and usage. Our target population is health care consumers that have usage and knowledge of EHR portals. To comprehend EHR portals adoption it is critical to:

- Understand what are the theories in the literature that can best support the understating of the EHR portals adoption and usage.
- Understand what are the significant constructs that can explain the adoption of EHR portals.

- Evaluate potentially different adoption drivers that emerge from different countries, which may be influenced by different health care strategies and governmental policies.

We expect that this dissertation will improve the knowledge of EHR Portal adoption, by suggesting a new research model that will include the most relevant drivers explaining their adoption. We developed four empirical studies that covered several theories and evaluated the EHR adoption in the European and US environment.

1.4 Research Goals

The main goal of this dissertation is to understand the drivers that lead to EHR portals adoption. With this purpose in mind we separate our aims by chapter. We subdivided the second Chapter into two sections. In the first we provide a description of the technology, and its relevance in the current health care environment. In the second we perform a literature review of the studies and theories that have focused on the adoption of EHR portals.

In the third Chapter, we analyse the determinants of EHR Portal adoption using UTAUT2. The main purposes are the following: to examine the importance of using an IT adoption consumer-specific model in a technology used by health care consumers; to analyse the extent of how relevant are the consumer-specific constructs in explaining the EHR Portal adoption and usage.

In the fourth Chapter, we extend the UTAUT2 model to include a specific construct related to the health belief model that could explain the underlying and specific health related motivations that may lead health care consumers to use EHR portals. By doing this we wish to evaluate if specific models deriving from the health environment may help to explain technologies such as EHR portals that support a more effective management of health-related tasks by the patients or health care consumers.

In the fifth Chapter, we concentrate our attention on understanding potential differences in the adoption drivers from two countries that follow different health care strategies, Portugal and the US. The US follows a specific type of health care system, the private health insurance (PHI) model coverage, which is based on private insurance only, which is also the major funding source (Bohm, Schmid, Gotze, Landwehr, & Rothgang, 2013). Portugal uses as a reference model a different approach, with the national health system (NHS) model that features universal coverage, with funding from general tax revenues and public ownership of the health infrastructure (Bohm et al., 2013).

We extended the UTAUT2 model with the CFIP framework to evaluate potential confidential concerns that may arise with the usage of EHR portals. According to the literature, in countries like the US where the regulation concerning data confidentiality is less strict compared with most European countries like Portugal where the regulation is tighter, significant differences may exist related with confidentiality when comparing the drivers of adoption between the two countries (Angst & Agarwal, 2009; Milberg, Smith, & Burke, 2000). In the US the dependence of having a health insurance and the direct out of pocket cost to have one, may lead to different cost-value perceptions compared to a country like Portugal, with NHS coverage (Bohm et al., 2013). This potential difference is expected to be measured by the UTAUT2 price value construct. Both countries were engaged at governmental level in initiatives to promote the adoption and use of EHR portals, however, the resources and investment done in the US were much greater than in Portugal (Blumenthal & Tavenner, 2010; Tavares & Oliveira, 2016b).

In the sixth Chapter we propose a refined new research model that combines the findings from the previous empirical studies. The new research model combines the UTAUT2 model, self-perception construct from the HBM, and DOI theory related constructs. To achieve the goal of making the new research model as much complete as possible to cover the significant adoption drivers and to be able to fulfill the goal of being parsimonious, we did not include CFIP framework or hedonic motivation construct from UTAUT2, which both showed no relevance in the previous empirical research. Recent literature from patient eHealth technologies also support the decisions taken (Angst & Agarwal, 2009; Kuo, Talley, & Ma, 2015; Mackert, Mabry-Flynn, Champlin, Donovan, & Pounders, 2016).

1.5 Methods

Taking into account the different philosophical perspectives, we may regard that this work presents characteristics consistent with those of positivism. With regard to research methodologies, we used the deductive approaches. The theoretical frameworks and quantitative methodologies used in this dissertation are described below.

1.5.1 Theoretical Frameworks

The first study is based on the UTAUT2 model (Chapter 3). The two next studies (Chapter 4 and Chapter 5) use extensions of the UTAUT2 model. The study in Chapter 4 uses UTAUT2 in combination with a construct supported by the HBM, and the study in Chapter 5 uses the UTAUT2 model with CFIP. The last study (Chapter 6) is a new research model that combines UTAUT2, DOI, and the HBM.

1.5.2 Quantitative Research Methods

The Chapter 3 study used a cross-sectional on-line survey design to assess the main determinants of EHR Portal adoption. The data collection was conducted in Portugal, targeting adult users of EHR portals. According to the literature, this technology is used by fewer than 7% of the total health care consumers or patients (Tavares & Oliveira, 2016b). 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, including sampling in places where the population should be more prevalent (Kalton & Anderson, 1986; Picot, Samonte, Tierney, Connor, & Powel, 2001). The literature also reports that the users of EHR portals have higher levels of education than the population average (Ancker, Osorio, et al., 2015; Or & Karsh, 2009; Roblin, Houston, Allison, Joski, & Becker, 2009; Zhang, Yu, Yan, & Ton A M Spil, 2015). As a result, we focused our sampling strategy on places where our target population (users of EHR portals) is more prevalent, and we therefore selected educational institutions. A total of 386 valid survey questionnaires were collected. The model was tested using Structural Equation Modeling (SEM), namely using a variance-based technique, i.e., Partial Least Squares (PLS). According to the guidelines (Hair, Hult, Ringle, & Sarstedt, 2014), our analysis followed two different steps, (i) reliability and validity assessment of the measurement model and (ii) structural model assessment.

An equivalent method was used in the study presented in Chapter 4 seeking to understand the determinants of EHR portals adoption. Namely the use of a cross-sectional on-line survey to collect the data, same sampling approach, PLS-SEM, and the same guidelines to test the model. A total of 360 valid survey questionnaires were collected.

The study presented in Chapter 5 also used a cross-sectional on-line survey to analyse the supporting model. The sampling approach followed the same strategy mentioned in the previous two chapters but in this study we collected the data from two different countries, the US and Portugal. The potential differences between the two countries were evaluated through PLS, multi-group statistical analysis. According to the guidelines (Hair et al., 2014), the global model and each specific country model followed the same two different steps (i) reliability and validity assessment of the measurement model and (ii) structural model assessment. We collected 597 valid responses, 270 in the US and 327 in Portugal.

The study presented in Chapter 6 used a different sampling methodology. The adult users of EHR portals in Portugal where selected based on a random generation of mobile phone numbers, and interviewed by computer assisted telephone interviews. Approximately 95% of the Portuguese adult population has a mobile phone, which makes this approach a suitable one to estimate the EHR Portal usage in Portugal (ANACOM, 2016; Vicente & Reis, 2009). The model was tested using PLS-SEM. According to the guidelines, our analysis followed two different steps, (i) reliability and validity assessment of the measurement model and (ii) structural model assessment. We collected 139 valid responses, a lower number than the previous studies, but still valid according to the guidelines to test the model (Hair et al., 2014).

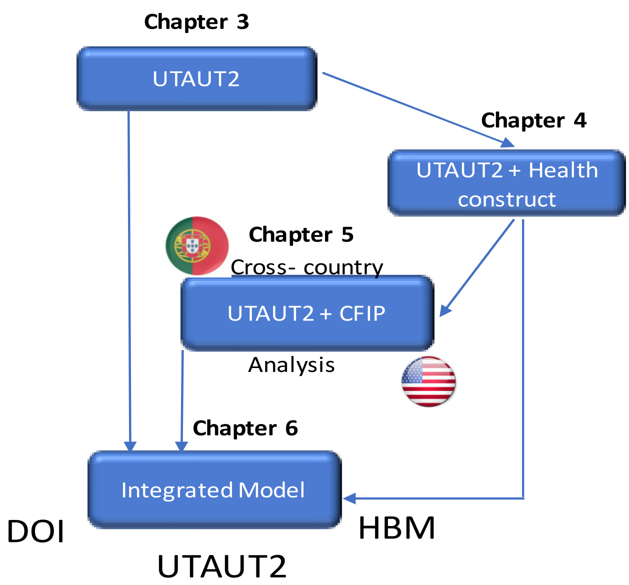


Figure 1.1 Empirical studies covered in this dissertation

1.6 Research Path

This dissertation gathers the findings of several research projects, reported separately, including three papers published in journals with double blind review process (indexed in Scimago and ISI Thomson Reuters), one book chapter, and one conference presentation. Additionally, one conference proceeding was also indexed at Scopus.

We subdivided the second Chapter into two sections. In the first section, we provide a description of the technology, and its relevance in the current health care environment. In the second section, we perform a literature review of the studies and theories that have focused on the adoption of EHR portals. The first section was published in the Encyclopedia of E-Health and Telemedicine as a book chapter. The second section was partially supported by the work presented in the 2nd IPleiria International Congress and published in the *Revista de Saúde Pública* (conference abstract). Chapter 3 was published in the *Informatics for Health and Social Care* (Scimago Q2). Chapter 4 was published in the *Journal of Medical Internet Research* (Scimago Q1/D1). Chapter 5 was published in *BMC Medical Informatics and Decision Making* (Scimago Q1). Chapter 6 has been submitted to a journal with double blind review process indexed in Scimago.

In the last chapter are the conclusions, which summarize and aggregate the findings from the different empirical studies presented in the previous chapters of this dissertation. With the exception of the last chapter, all other chapters are supported by work published in scholarly publications with double blind review process, including first quartile (Q1) journals. This can be regarded as a positive indication of the work quality that supports this dissertation. The highest quartile range reported to each journal concerns the latest available Scimago ranking (2016).

Table 1.1 Studies current stage

Chapter	Study Title	Current Stage
Chapter 2	Electronic Health Record Portals Definition and Usage	Published as a book chapter in the Encyclopedia of E-Health and Telemedicine
Chapter 3	Electronic Health Record Portals adoption: Empirical model based on UTAUT2	Published in *Informatics for Health and Social Care*
Chapter 4	Electronic Health Record Patient Portal Adoption by Health Care Consumers: An Acceptance Model and Survey	Published in the *Journal Medical Internet Research*
Chapter 5	Electronic Health Record Portal Adoption: a cross-country analysis	Published in *BMC Medical Informatics and Decision Making*
Chapter 6	Electronic Health Record Portal Adoption- A New Integrated Model Approach	Submitted

Chapter 2- Electronic Health Record Portal Definition and Literature Review

2.1 Chapter Scope

Electronic Health Record (EHR) portals are a recent technological approach receiving great attention by several governments worldwide (Bush et al., in press; Gheorghiu & Hagens, 2017). In Europe there are ongoing initiatives allowing the sharing of patient EHR information between the EU countries, and in the US the multi-billion-dollar initiative "Meaningful Use", strongly encourages the health care providers to grant direct access to the patient EHR (Bush et al., in press; Gheorghiu & Hagens, 2017). With these changes happening it is very important to explain their relevance in the current international health care environment. Also, the terminology, and the concept are not uniform between different studies and countries. Some mention it as EHR patient portals, others as EHR portals, and even others use more IT specific terminologies such as EHR-tethered portals (Ancker, Osorio, et al., 2015; Jhamb et al., 2015; Otte-Trojel et al., 2014; Tavares & Oliveira, 2017).

With these initiatives, governments are implementing new innovative measures via EHR portals, allowing patients to have digital access to their medical records, increasing patient empowerment, and making EHR portals a truly patient-centred tool. The EHR portals definition and the explanation of their relevance in the current international health care environment, make this topic important by itself to be published as a book chapter, and we present it as a first section in this dissertation chapter. In the second section, we perform a specific literature review that covers the last three years that encompass the most intense period of EHR portals implementation and we then provide recommendations for future research avenues (Kern, Edwards, Kaushal, & Investigators, 2016; Nambisan, 2017).

2.2 Electronic Health Record Portals Definition and Usage

2.2.1 Introduction

The eHealth technology for health care consumers is the use of electronic resources, mainly web-based, on medical topics by healthy individuals or patients (Alpay et al., 2010; Lee, Gray, & Lewis, 2010; Millard & Fintak, 2002). Our study focuses on a specific type of eHealth technology, the EHR portals, which give patients access to medical records, exam results, and services, such as appointment scheduling, notification systems, and e-mail access to the doctor (Andreassen et al., 2007; Angst & Agarwal, 2009; Tavares & Oliveira, 2014b; Weingart et al., 2006). Understanding the acceptance and use of eHealth technology by health care consumers is a very relevant topic with clear benefits for the society and future sustainability of the Health Care System (Or & Karsh, 2009; Wilson & Lankton, 2004). The warning signs are that the number of patients with chronic diseases is projected to grow by 45% between 2007 and 2025 and the workforce will be 10% smaller (Alpay et al., 2010; Tavares & Oliveira, 2014a). Combining these two trends, there will be less health professionals available in the future to support patients. EHR portals may help patients carry out self-management activities making the use of the healthcare system more effective and sustainable, not only from the patient care standpoint, but also from the financial perspective due to the increasing cost of the healthcare budget in the different countries (Alpay et al., 2010; EU Commission, 2004; McKee, Karanikolos, Belcher, & Stuckler, 2012; Metaxiotis, Ptochos, & Psarras, 2004; Tavares & Oliveira, 2014b).

The goal of this chapter is to provide a clear definition of EHR portals, their advantages, current usage and provide insights of strategies to increase their use.

2.2.2 Background

To better understand the definition of EHR portals it is important to have a clear view of the technologies that support them. The first one are the patient portals, healthcare-related online applications that allow patients to interact and communicate with their healthcare providers (Weingart et al., 2006). EHR means a repository of patient data in digital form, stored and exchanged securely. It contains retrospective, concurrent, and prospective information and its primary purpose is to support continuing, efficient and quality integrated health care (Hayrinen, Saranto, & Nykanen, 2008). EHRs may include a range of data, such as medical history, medication and allergies, immunization status, laboratory test results, radiology images, vital signs, personal statistics like age and weight, and billing information (Angst & Agarwal, 2009; Hayrinen et al., 2008). EHR systems are the software platforms that physician offices and hospitals use to create, store, update, and maintain EHRs for patients (Angst & Agarwal, 2009). By definition an EHR Portal is a web based application that combines an EHR System and a Patient Portal, not only to enable patients to interact with their healthcare providers (schedule medical appointments, send messages to their physicians, request prescription refills online) but also to access their medical records and medical exam results (Angst & Agarwal, 2009; Tavares & Oliveira, 2014b; Weingart et al., 2006). Table 2.1 provides an overview of the definition, differences and commonalities between EHR portals and EHR systems.

Table 2.1 Definition, differences and commonalities between EHR portals and EHR systems (Bisbal & Berry, 2011; Blobel & Pharow, 2008; Weingart et al., 2006)

	EHR Portal	EHR System
Definition	Web based application that combines an EHR System with a Patient Portal that enables several functionalities such as: request prescription refills, schedule medical appointments, email messaging, and disease management information areas.	It is an IT platform for realizing the mechanisms of creating, using, storing, and retrieving an EHR. EHR systems have to be based on an Architecture that enables them to be communicable, comprehensive, useful, and ethically compliant.
Differences	The aim of the EHR Portal is to give patients access to their clinical data and to enable the communication between the patients and the healthcare providers. Patient centred technology	The EHR System focus is to provide access to clinical integrated information to the healthcare professionals. Healthcare professional centred technology.
Commonalities	Both of the technologies use patients EHR. The main building block of an EHR Portal is the EHR System that with its interoperability capability may enable the EHR portals to communicate.	

2.2.3 Current Implementation and Use

A recent survey of United States (US) healthcare providers showed that 57% of healthcare institutions already have a portal in place and 71% value the integration of the EHR system within the Patient Portal by choosing a product (patient portal interface) from their EHR vendor (Allphin, 2012). In Europe, not only healthcare providers such as hospitals and clinics provide EHR portals, but also governmental institutions provide these platforms to the patients (Alpay et al., 2010; Rodrigues, Lopes, & Tavares, 2013; Tavares & Oliveira, 2014b). This concept of national level Patient Portal, progressed into a trans-European initiative, the European Patients Smart Open Services (epSOS). EpSOS concentrates on developing a practical eHealth framework and Information and Communication Technology (ICT) infrastructure that enables secure access to patient health information among different European healthcare systems (epSOS, 2014). The pilot stage of this project that ended in June 2014 focused on cross-border eHealth services in the following areas: patient summary (access to important medical data for patient treatment) and cross-border use of electronic prescriptions (epSOS, 2014).

In the US a new guidance was issued by the Center for Medicare & Medicaid Services (CMS), called stage 2 meaningful use (HealthIT.gov, 2014). This guidance requires that the eligible professionals and hospitals that participate in Medicare and Medicaid EHR Incentive Programs must give their patients secure online access to their health information, including EHRs (Allphin, 2012; HealthIT.gov, 2014). Stage 2 meaningful use, boosted the development of new integrated EHR portals in the US by health care providers, who according to the new guidance, must not only implement it but also demonstrate effective use by the patients (Allphin, 2012; HealthIT.gov, 2014).

According to the literature the most used features in EHR patient portals are: schedule medical appointments, email messaging, request prescription refills and online check of medical exams (Andreassen et al., 2007; Irwin, 2014; Weingart et al., 2006).

2.2.4 Issues and Opportunities

According to several studies, the use of web-based technologies for healthcare in Europe and the US is between 30% to 50% (Alpay et al., 2010; Andreassen et al., 2007; Irwin, 2014; Tavares & Oliveira, 2014b). Nevertheless, in the specific case of EHR portals the use of this specific technology seems to be lower (Angst & Agarwal, 2009; Ministério da Saúde, 2012). To successfully attest for meaningful use stage 2, healthcare providers must have an EHR Portal that is used by at least 5% of patients in order to receive financial incentives (HealthIT.gov, 2014;

Irwin, 2014). Reports have shown that providers have struggled with patient portal adoption which caused CMS to lower the objective to 5% from the initial 10% (Allphin, 2012; Irwin, 2014). In Europe, cases like “Portal do Utente”, nationwide EHR portal for the Portuguese National Health System (NHS), with several functionalities (request prescription refills, schedule medical appointments, medical records, email messaging, disease management information areas), still have less than 10% of the potential users registered (Ministério da Saúde, 2012). With the worldwide increase in healthcare spending the adoption and use of EHR portals, exemplifies a tool that can be an opportunity to increase the efficiency, reduce costs, and enable better communication between the health care providers and patients (Allphin, 2012; Alpay et al., 2010; Tavares & Oliveira, 2014b; Weingart et al., 2006; Wilson & Lankton, 2004). EHR portals help patients carry out self-management activities, have access to their medical records and exams and facilitate their daily life by having a quicker and easier point of contact with healthcare professionals and institutions (Tavares & Oliveira, 2014b; Weingart et al., 2006). For example, if a chronic patient requires a prescription refill and can request it via EHR Portal, the patient avoids the time and cost of appointment scheduling and the trip to the clinical institution. The healthcare providers also avoid the time and cost of administrative procedures that can be done easily online (Weingart et al., 2006; Wilson & Lankton, 2004). There are multiple practical examples of benefits of EHR portals for both patients and healthcare providers. It is then fundamental to understand the critical determinants that can lead to a higher usage and adoption of EHR portals.

Another important issue that is critical to the success of the EHR portals is that many of the EHR systems that support them are not concerned with interoperability (Bisbal & Berry, 2011; Goeg, Cornet, & Andersen, 2015). This refers to the ability to exchange information between systems. The level of interoperability can be raised if systems agree on the structure of the information to be exchanged. This is often called functional interoperability, the only objective of which is to transfer information so that is humanly readable by the receiver (Bisbal & Berry, 2011). Nevertheless, the main goal is that two systems that need to exchange information agree on exactly the structure of the information to be exchanged, and more importantly, on the meaning of all the information to be exchanged. This is the goal of semantic interoperability (Bisbal & Berry, 2011). Currently, it is believed that semantic interoperability can only be achieved through standardization of data models, clinical data structure, and terminologies (Bisbal & Berry, 2011; Goeg et al., 2015). The momentum of this approach is being exemplified by current standardization efforts at CEN (standard EN-13606, known as EHRCom) as well as HL7 (RIM version 3) (Bisbal & Berry, 2011; Blobel & Pharow, 2008; Goeg et al., 2015).

2.2.5 Solutions and Recommendations

EHR portals are a very important technology that brings benefits to both patients and healthcare providers (Tavares & Oliveira, 2014b). Nevertheless, there is a need to increase EHR portals use (Allphin, 2012; HealthIT.gov, 2014), which can be achieved by understanding the determinants of adoption of these web-based platforms by patients. The drivers of adoption in eHealth are different from other IT technologies and in the case of EHR portals incorporate the consumer perspective (Angst & Agarwal, 2009), since a patient is a health care consumer (Lee et al., 2010). Ideally, we need a new model tailored to the EHR portals particularities, focused on the consumer use context, such as the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2), (non-specific of eHealth) but also incorporating constructs that can be specific to eHealth technologies (Alvesson & Kaerreman, 2007; Venkatesh et al., 2012). The results of this new model should be used to incorporate improvements in EHR portals than can lead to greater use of these web-based platforms by patients (Tavares & Oliveira, 2014b).

2.2.6 Future Research Directions

The development and proposal of a new adoption model tailored to EHR portals it is a complex task that will require a deeper literature review and the application and validation of the model to a set of health care consumers, in order to test the framework developed and directly assess its explanatory and predictive power. Future studies may evaluate other relationships that were not foreseen in the initial model and that will improve the ability to explain the dependent variables. Refinement of the constructs and measures is one of the other possibilities. Testing the new model in other countries may show differences between countries concerning the critical determinants for adoption of EHR Portals.

Nevertheless there is also a very important topic to be addressed, which is the interoperability between the different EHR portals that very often is not possible because there are different providers of EHR systems (Allphin, 2012; Hayrinen et al., 2008). Another future research direction to be followed is to achieve interoperable EHR systems from EHR portals.

2.2.7 Conclusion

Understanding the acceptance and use of EHR portals by health care consumers should bring strong benefits for the future sustainability of the Heath Care System, which will enjoy more efficient use of resources. By definition an EHR Portal is a web based application that combines an EHR System and a Patient Portal. Some of the most important features of EHR portals are: schedule medical appointments, electronic messaging between health professionals and patients, request prescription refills, and online access to medical records and exams results (Weingart et al., 2006). Although the use of the internet for health topics is widespread worldwide in the specific case of EHR portals the adoption is still lower than expected by governments and healthcare institutions (Angst & Agarwal, 2009; Tavares & Oliveira, 2014a). Important projects and guidance's like epSOS in Europe and stage 2 meaningful use in the US have the goal of increasing the use of EHR portals by patients and health care consumers. The eHealth technology adoption, and more specifically EHR portals, differentiates from IT adoption in general due to the sensitive topics and issues related to health status of an individual, making the drivers of EHR portals adoption different from other IT technologies (Angst & Agarwal, 2009; Tavares & Oliveira, 2014a). We propose that a new adoption model specifically tailored to EHR portals should be developed incorporating IT consumer adoption-related constructs plus eHealth specific constructs. The new model should be tested in different EHR portals and countries to check for potential differences concerning the adoption of these web-based platforms. The outcomes of this new model should be used to incorporate improvements in EHR portals, which should lead to greater use of these web-based platforms by patients.

2.3 Electronic Health Record Portal Adoption: A Literature Review

2.3.1 Introduction

In the previous section, we presented the EHR portals concept and explained their relevance in the current international healthcare environment. In this section we perform a literature review. Especially important to the EHR portals development and for the patients are the so called "stage 2 meaningful use" that started in 2014 (Black et al., 2015) and the European Patients Smart Open Services (epSOS), which ended the project stage in June 2014 . Stage 2 meaningful use increased the growth of new integrated EHR portals in the US by healthcare providers who, according to the new guidance, must not only implement it but also prove effective usage by the patients (Ancker, Brenner, Richardson, Silver, & Kaushal, 2015; Black et al., 2015; Kern et al., 2016; Tavares & Oliveira, 2016b). In Europe, a trans-European initiative, the European Patients Smart Open Services (epSOS) focused on developing a practical eHealth framework and Information and Communication Technology (ICT) infrastructure that enables secure access and share of patient health information amongst different European healthcare systems (epSOS, 2014; Tavares & Oliveira, 2016b). In the last three years significant institutional and governmental initiatives have occurred to provide patients secure access to their EHR via web based portals (Ancker, Brenner, et al., 2015; Black et al., 2015; Tavares & Oliveira, 2016b). Ultimately it is very important to understand how these policies have impacted the adoption of the EHR portals in the last three years and what the influential factors to health care consumers adoption of this new technology are. We focus our review in this time frame.

According to the literature, understanding the adoption of a new IT tool with the complexity that surrounds the handling of patient data, makes the use of adoption models and structural equation modelling (SEM) a valuable approach to understand this phenomenon (Angst & Agarwal, 2009; Kim & Park, 2012).

The goal is to identify the research, theories, and factors that have led healthcare consumers to adopt EHR portals, using adoption models supported by an empirical quantitative approach, preferably using structural equation modelling.

2.3.2 Methodology

Following literature recommendations and systematic reviews in eHealth adoption (Li et al., 2013) we conducted a literature review following four steps: (1) identification of resources, (2) selection of relevant papers, (3) data extraction and analysis, and (4) validation.

Identification of Resources

A literature search was done between July 2014 and July 2017 using two online database sources: PubMed, and the Online Knowledge Library (B-on). B-on itself is an academic search engine with access to more than 16,700 scholarly journals, conference proceedings and ebooks (B-on, 2017) that consolidates information from other reference databases (e.g: Annual Reviews; Academic Search Complete; Association for Computing Machinery; Business Source Complete; Elsevier; Eric; IEEE; Web of Science, ISI Proceedings; Nature; Sage; Springer; Taylor and Francis; Wiley and Zentralblatt). These databases cover not only work published in information systems adoption literature but also specific health care databases (e.g. PubMed) that also cover eHealth adoption related work. All search fields available from each search service were used. In each database, the search was repeated using the following phrases: ["Patient Portals" AND "EHR" AND "Structural Equation Modelling"] or ["Patient Portals" AND EHR AND Adoption]

Selection of Relevant Articles

The full texts of the identified papers were reviewed for relevance. Papers with the following features were excluded from further analysis:

1. articles not written in English.
2. articles that did not directly use the terms “Adoption”, “EHR”, and “Patient Portals” or related terms in the title, abstract, or entire text, with casual referencing of EHR portals usage related issues.
3. articles without empirical evidence.
4. studies addressing technologies that do not allow patients to access their medical records or exam results.
5. articles that discussed adoption or user acceptance under the scope of the study topic but not from the consumer health care (patient) perspective.

Table 2.2 Identification of papers for review from the online databases

Keywords	PubMed	B- on	Total	Duplicated Results
Patient Portals AND EHR AND Structural Equation Modelling	0	694	694	0
Patient Portals AND EHR AND Adoption	13	2075	2075	13
Total unrepeated articles retrieved	13	2224	2224	558

For all the searches within B-on we removed the non-academic results (e.g. news and commercial reports). Another potential issue is that B-on works as a search engine retrieving data from other databases, and duplicates are possible to occur. We also removed all duplicates from the results we obtained with B-on. The results in Table 2.2 for B-on already include this cleansing work. We started our research with a narrow keywords approach [“Patient Portals” AND “EHR” AND “Structural Equation Modelling”], and although we identified many papers (694), we decided to use an additional and less stringent keyword approach [“Patient Portals” AND “EHR” AND “Adoption”], to attempt to include the maximum number of results for analysis in order to avoid losing relevant papers. All results obtained in PubMed were also in B-on. In total 42 documents were identified that did not included the immediate exclusion features mentioned above.

From the large number of documents, we examined, many of them did not follow an empirical approach, and are just review articles about our study topic. Others use the patient as target population but study eHealth or internet adoption by the patient, but are not specific about EHR portals. Several excluded studies also mentioned the use of EHR portals but from the perspective of the healthcare professionals and not the patient. Particularly within the B-on search several documents were excluded because they made casual reference to the search keywords but without any meaning to our study goal. Figure 2.1 shows the literature review steps.

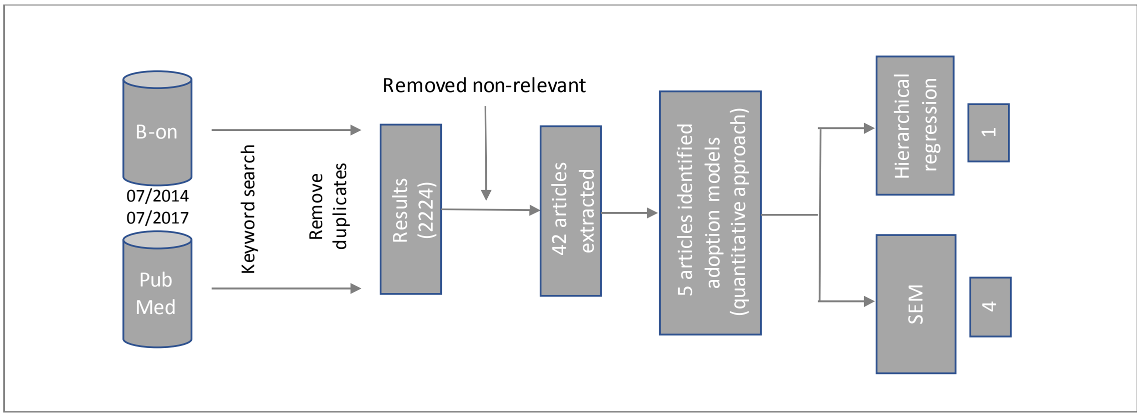


Figure 2.1 Literature review steps flow

Data Extraction and Analysis

Most of the studies identified are originally from the US, as seen in Table 2.3, and that may be explained by the significant investment that the federal government made to promote the usage of EHR, and specifically with “stage 2 meaningful use”, that required their on-line access by the patients (Nambisan, 2017; Reicher & Reicher, 2016).

Table 2.3 Articles identified by geographic origin and type

Geography origin	**US**	**Europe [b]**	**Australia**	**Asia**
Frequency	34 (80.9%)	5 (11.9%)	2 (4.8%)	1 (2.4%)
Study Type	**Qualitative**	**Mix- Approach [a]**	**Quantitative**	**Quantitative with Adoption Models**
Frequency	10 (23.8%)	3 (7.1%)	24 (57.2%)	5 (11.9%)

Notes:

1. [a] uses a qualitative and quantitative approach; [b] one of the studies is originally from Europe but also covers one sample of US EHR Portal users.

The most common methodological approach is the quantitative. We sub-divided the quantitative approach with and without using adoption models, to enable a better identification of the studies that attempted to understand in a more structured approach the underlying complexity of EHR Portal adoption. Most of the quantitative studies focused on understanding the usage patterns of EHR portals, correlating them with users' socio-demographic characteristics (Bush et al., in press; Gordon & Hornbrook, 2016; Riippa, Linna, Ronkko, & Kroger, 2014; Smith et al., 2015). Possibly the main reason for a greater emphasis on pure usage metrics is that "stage 2 meaningful use" required the healthcare providers to demonstrate effective usage of EHR portals, and since most of the literature identified is from the US, it drove the published literature in this direction.

Table 2.4 Information about the studies that used adoption models with a quantitative approach

Study Title	Sample Geography	Theory	Dependent Variable	Statistical Approach	Findings	Reference
Electronic Health Record Portal Adoption: a Cross Country Analysis	US and Europe	Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) Plus Concern for Information Privacy (CFIP)	Behavioural intention and use behaviour in EHR portals	Structural equation modelling	▪ Study identified critical factors for the adoption of EHR portals and significant differences between US and Portugal. ▪ The statistically significant factors of behavioural intention are performance expectancy, effort expectancy, social influence, hedonic motivation, price value, and habit. The predictors of use behaviour are habit, and behavioural intention. ▪ Social influence, hedonic motivation, and price value are only predictors in the US group. ▪ The EHR portals usage patterns are significantly higher in US compared to Portugal. ▪ Confidentiality issues do not seem to influence acceptance.	(Tavares & Oliveira, 2017)
Electronic Health Record Patient Portal Adoption by Health Care Consumers: An Acceptance Model and Survey	Europe	UTAUT2 extended model	Behavioural intention and use behaviour in EHR portals	Structural equation modelling	▪ Effort expectancy, performance expectancy, habit, and self-perception are predictors of behavioural intention. ▪ Habit and behavioural intention are predictors of use behaviour.	(Tavares & Oliveira, 2016a)
Social Influence on Health IT Adoption Patterns of the Elderly: An Institutional Theory Based Use Behaviour Approach	US	New model supported by Institutional Theory and Unified Theory of Acceptance and Use of Technology (UTAUT)	Patient Portal use behaviour	Structural equation modelling	▪ Coercive and mimetic pressures significantly influence patient portal use behaviour. ▪ Normative pressure was found to be not relevant.	(Bozan, Davey, & Parker, 2015)

Study Title	Sample Geography	Theory	Dependent Variable	Statistical Approach	Findings	Reference
Awareness and Use of the After-Visit Summary Through a Patient Portal: Evaluation of Patient Characteristics and an Application of the Theory of Planned Behaviour	US	Theory of Planned Behaviour (TBP)	Intention to access the after –visit summary (AVS)	Hierarchical multiple regression	▪ Intention to access the AVS through the portal was significantly influenced by attitude, perceived norm, and perceived behavioural control.	(Emani et al., 2016)
A structural model of information privacy concerns toward hospital websites.	Taiwan	Information privacy concerns plus organization reputation	Information privacy concerns	Structural equation modelling	▪ Significant predictors of information privacy concerns include a stated online privacy policy and hospital's reputation. ▪ The study confirmed that an online privacy policy and reputation can effectively reduce information privacy concerns.	(Kuo et al., 2015)

Of the studies mentioned in Table 2.4, four used SEM and one used hierarchical multiple regression. Overall, the use of SEM to study the adoption of EHR portals is not a common approach, with also two of the studies mentioned in Table 2.4 by the authors of this literature review. The research models and theories presented in Table 2.4 include the Theory of Planned Behavior (TPB), Unified Theory of Acceptance and Use of Technology (UTAUT), and UTAUT2. UTAUT2 provides a unified view of several existing IT adoption theories plus consumer specific constructs (Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh et al., 2012). A recent study included in Table 2.3 used UTAUT2 with a qualitative approach to study older people's adoption of EHR Portals, providing more evidence about UTAUT2 usefulness (Arauwou, 2017). In this specific study with older adults, the need to provide training to them on how to use the portal (facilitating conditions), the caregivers' influence to promote the usage of the portals (social influence), and the promotion of continuous usage (habit) via the physicians' frequent correspondence to the older adults via the portal, were highlighted to be the most important dimensions to promote adoption and usage in older adults (Arauwou, 2017). Also reported in Table 2.4, privacy concerns related with the patient access to EHR portals were also evaluated (Kuo et al., 2015) as well as drivers related with the specific individual perception of their own current health condition as promoting the adoption of EHR portals (Tavares & Oliveira, 2016a). Other studies included in Table 2.3 also mentioned health literacy (Smith et al., 2015), and frequent internet health information seeking as drivers for the adoption of EHR portals (Mackert et al., 2016; Nambisan, 2017; Smith et al., 2015; Tavares & Oliveira, 2016a). Also, two qualitative studies successfully used the diffusion of innovation (DOI) theory to explain the adoption of our target technology (Xiaojun, Ping, & Jun, 2014; Zhang et al., 2015). Regarding users' socio-demographic characteristics there is a consistent trend to be younger and more educated than the population average (Ancker, Osorio, et al., 2015; Smith et al., 2015; Zhang et al., 2015).

Table 2.5, adds more relevant information to the literature review because identifies the statistically significant constructs with a direct impact on behavior intention and use behavior, the most relevant dependent variables. Although the number of studies is limited, the constructs from UTAUT and the ones specific from UTAUT2 according to Table 2.5 have a statistically significant role explaining EHR portals adoption. Although facilitating conditions is not mentioned, perceived behavioural control is according to the literature an equivalent to facilitating conditions and with a statistically significant impact as reported in Table 2.5 (Venkatesh et al., 2003). The same between perceived norm and social influence (Venkatesh et al., 2003). Information privacy concerns have a negative impact on behavioural intention to adopt EHR portals. Also the health care institution reputation besides having a positive impact on behavioural intention to adopt EHR portals, also attenuates the confidentiality concerns (Kuo et al., 2015). Mimetic pressure ("the conscious and voluntary act of copying behaviors of those with higher status and success" (Bozan et al., 2015, p. 520)) and coercive pressure ("formal and informal pressures on an individual by a more powerful individual to adopt the same practices" (Bozan et al., 2015, p. 520)) from Institutional Theory (Bozan et al., 2015), have according to the authors of the study a similar conceptual impact as social influence from UTAUT (Bozan et al., 2015). Although attitude had a significant impact on behavioural intention in one of the studies (Emani et al., 2016) it is known from the literature that attitudinal constructs are often statistically significant only when particular cognitions—in this case, constructs related to performance expectancy and effort expectancy— are not included in the model (Bozan et al., 2015).

Performance expectancy and effort expectancy from UTAUT also have its equivalents from DOI, as relative advantage and complexity (Bozan et al., 2015). Also, self-perception a construct deriving from the Health Belief Model (HBM) shows a statistically significant impact on behavioural intention to adopt EHR portals.

Table 2.5 Constructs with significant results on behavioural intention and use behaviour

Study Title		Electronic Health Record Portal Adoption: a Cross Country Analysis (Tavares & Oliveira, 2017)	Electronic Health Record Patient Portal Adoption by Health Care Consumers: An Acceptance Model and Survey (Tavares & Oliveira, 2016a)	Social Influence on Health IT Adoption Patterns of the Elderly: An Institutional Theory Based Use Behaviour Approach (Bozan et al., 2015)	Awareness and Use of the After-Visit Summary Through a Patient Portal: Evaluation of Patient Characteristics and an Application of the Theory of Planned Behaviour (Emani et al., 2016)	A structural model of information privacy concerns toward hospital websites (Kuo et al., 2015).
BI						
	PE[a,d]	X	X			
	EE[a,d]	X	X			
	SI[a]	X				
	PC				X	
	HT[b]	X	X			
	HM[b]	X				
	PV[b]	X				
	SP[c]		X			
	IC[e]					X
	RP					X
	AT				X	
	PN				X	
UB						
	BI[a]	X	X			
	CP			X		
	MP			X		
	HT[b]	X	X			

Notes:

1. X: $P < 0.05$;
2. PE: Performance Expectancy; EE: Effort expectancy; SI: Social influence; PC: Perceived behaviour control; HT: Habit; HM: Hedonic motivation; PV: Price value; SP: Self- perception; IC: Information privacy concerns; RP: Reputation; AT: Attitude; PN: Perceived norm; BI: Behavioural intention; CP: Coercive pressure; MP: Mimetic pressure; UB: Use behaviour.
3. [a] UTAUT constructs; [b] UTAUT2 consumer specific constructs; [c] health related construct; [d] DOI constructs; [e] Confidentiality constructs

Validation

The database search using the specific keywords mentioned and the study analysis and extraction of the relevant papers was first be performed by one of authors and repeated by the other author, who validated the results.

2.3.3 Discussion

The use of structural equation modeling to study adoption has increased substantially in the last five years in many areas (e.g. Information Systems, Banking, Marketing) (Hair, Hult, Ringle, & Sarstedt, 2017). The use of adoption models using SEM in eHealth related technologies has also increased, but with a greater emphasis on the ones that used healthcare professionals as the target population (Ahadzadeh et al., 2015; Behkami & Daim, 2016; Tavares & Oliveira, 2017). Before 2014 and stage 2 meaningful use, very few patient portals in the US incorporated EHR access to the patients (Otte-Trojel et al., 2014) and the situation in other developed countries in the world was similar (Gheorghiu & Hagens, 2017; Otte-Trojel et al., 2014). A recent literature review that focused on the use of patient portals in the management of chronic disease for a period of 10 years (2004-2014), identified 27 relevant papers and none used adoption models with SEM (Scott, Argueta, Lopez, & Nair, 2015). This is clearly a specific technology in which adoption models and more specifically, their analysis with SEM is not frequent.

As EHR portals are healthcare consumer focused technology, the use of UTAUT2, addresses this need (Bush et al., in press; Tavares & Oliveira, 2016a; Venkatesh et al., 2012). From the literature review it was possible to identify other theories and dimensions that can be useful to understand EHR portals, being a specific eHealth tool, drivers related with health- related behaviors seem to influence the adoption of EHR portals (Mackert et al., 2016; Nambisan, 2017; Smith et al., 2015; Tavares & Oliveira, 2016a). The management of personal medical data is a sensitive topic, and confidentiality concerns were also identified in the literature review as important to be covered when studying EHR portals adoption (Kuo et al., 2015; Mackert et al., 2016; Tavares & Oliveira, 2017). EHR portals is a recent technology with a still low adoption rate. The literature review also identified DOI as potential theory to explain the adoption of EHR portals (Xiaojun et al., 2014; Zhang et al., 2015). Although the number of studies published using adoption models is still limited their evidence, points to the need to have a patient centred model, that should be able to cover additional dimensions related with the health behavior, confidentiality concerns and innovation drivers.

2.3.4 Suggested Models

EHR portals are a healthcare consumer centred technology, demanding a model that is consumer centric. According to the literature findings, UTAUT2 is a good approach to evaluate EHR portals (Arauwou, 2017; Tavares & Oliveira, 2016a; Venkatesh et al., 2012)

UTAUT2 Model

UTAUT2 is an extension of the UTAUT model, one of the most cited models in IT adoption (Venkatesh et al., 2012). UTAUT2 covers the consumer approach into IT adoption whereas UTAUT was conceived having as the main goal studying employee technology acceptance at the individual level (Venkatesh et al., 2012). UTAUT2, contains the four original constructs of UTAUT, plus an additional three that are regarded as consumer specific (Venkatesh et al., 2012). The constructs are moderated by age, gender, and experience according to how it is described in Figure 2.2 (Venkatesh et al., 2012). The arrows in Figure 2.2 indicate the relationships between the constructs in the model.

The four constructs from UTAUT are performance expectancy, effort expectancy, social influence, and facilitating conditions (Venkatesh et al., 2003). Performance expectancy is defined as the perceived benefits that an individual obtains by using a technology in a certain activity (Venkatesh et al., 2003). Effort expectancy is associated with how easy it seems to be to use a certain technology (Venkatesh et al., 2003). Social influence is the extent to which consumers perceive that others who are important to them believe they should use a technology (Venkatesh et al., 2003). Facilitating conditions is defined as the individual perception of the support available in order to use a technology (Venkatesh et al., 2003).

The three additional consumer- specific constructs from UTAUT2 are hedonic motivation, price value, and habit. Hedonic motivation is defined as the intrinsic motivation of an individual to obtain fun or pleasure from using a technology (Venkatesh et al., 2012). Price value is defined as the perceived benefits of using a technology given its costs (Venkatesh et al., 2012). Habit refers to the automatic nature of a behaviour response resulting from learning (Venkatesh et al., 2012) . Compared to UTAUT, the three new consumer- specific constructs proposed in the original UTAUT2 study produced a substantial improvement in the variance explained in behavioural intention (from 56% to 74%) and use behaviour (from 40% to 52%) (Venkatesh et al., 2012).

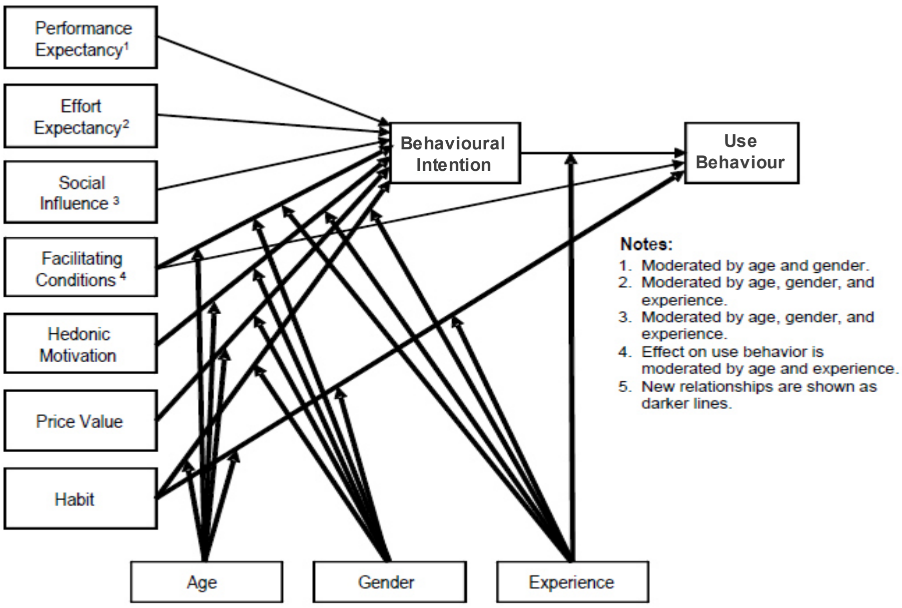


Figure 2.2 UTAUT2 model (Venkatesh et al., 2012)

Confidentiality concerns is an additional topic also addressed in the literature when studying EHR portals adoption (Kuo et al., 2015; Mackert et al., 2016). Angst and Agarwal (2009) used the Concern for Information Privacy (CFIP) framework to predict the confidentiality concerns related with the adoption of EHR by the patients taking in account the future implementation of the meaningful use program in the US and potential strategies to overcome confidentiality concerns (Angst & Agarwal, 2009). This highly cited study, published in *MIS Quarterly* (Angst & Agarwal, 2009), was done immediately before the meaningful use implementation (Angst & Agarwal, 2009; Tavares & Oliveira, 2017). There is also evidence in the literature that different levels of regulation regarding EHR data confidentiality may lead to different perceptions regarding confidentiality impact in the adoption of EHR between a more strict and regulated Europe versus US (Angst & Agarwal, 2009; Milberg et al., 2000).

CFIP Framework

The CFIP framework was originally developed to measure beliefs and attitudes concerning individual information privacy related to the use of personal information in a business environment (Smith, Milburg, & Burke, 1996). It was conceptualized as being composed of four dimensions: collection, errors, unauthorized access, and secondary use (Smith et al., 1996). Collection is the concern that an extensive amount of personal information is being collected and stored in databases (Smith et al., 1996). Errors are directly linked with the concern that protection against deliberate and accidental error in personal data is inadequate (Smith et al., 1996). Unauthorized access is the concern that data about individuals are available to people not authorized to view or work with those data (Smith et al., 1996). Finally secondary use refers to the apprehension that information is collected from individuals for one purpose but is subsequently used for another purpose without approval from the individuals (Smith et al., 1996). Lately Stewart and Segars (2002) expanded the original framework and not only validated the multidimensional nature of the CFIP construct, but also found support for the hypothesis that a second-order factor structure is also empirically valid (see Figure 2.3). Both approaches are reported in the literature as feasible (Angst & Agarwal, 2009; Ermakova, Fabian, Kelkel, Wolff, & Zarnekow, 2015; Tavares & Oliveira, 2017).

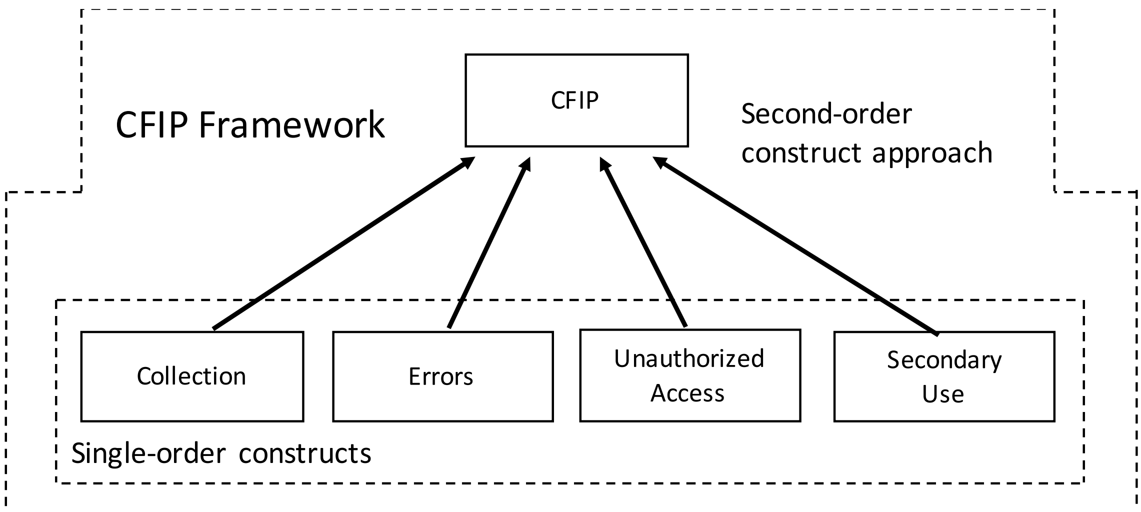


Figure 2.3 CFIP Framework with first-order (Smith et al., 1996) and second-order construct approach (Stewart & Segars, 2002)

HBM Theory

According to the literature, drivers related with health-related behaviours seem to influence the adoption of EHR portals (Nambisan, 2017; Tavares & Oliveira, 2016a). The HBM, has been used successfully within patient centred technologies and should be an important theory to evaluate within the scope of studying EHR portals adoption (Ahadzadeh et al., 2015; Kim & Park, 2012).

The HBM suggests that the belief in a health risk predicts the likelihood of engaging in health-related behaviour (Janz & Becker, 1984; Jones et al., 2015). The HBM posits that six constructs predict health behaviour: perceived susceptibility, perceived severity, perceived benefits, perceived barriers, self-efficacy, and cues to action (Jones et al., 2015). Perceived susceptibility means that individuals will engage in actions to prevent a health problem if they regard themselves as susceptible to a condition (Champion & Skinner, 2008; Jones et al., 2015). Perceived severity can be defined by when people believe that a health problem may have potentially serious consequences (Jones et al., 2015). Perceived benefits refer to an individual's assessment of the value of engaging in a health-promoting behaviour to reduce the risk of a specific health concern (Champion & Skinner, 2008; Jones et al., 2015). Perceived barriers is linked to the individual's perceived negative attributes related to the health action (e.g. medication with side effects) (Champion & Skinner, 2008; Jones et al., 2015). The HBM also states that a cue is necessary to start engagement in health-promoting behaviour. These cues to action can be internal or external, ranging from having illness symptoms to exposure to a health campaign (Jones et al., 2015). Self-efficacy was added to the model later (Jones et al., 2015). Self-efficacy refers to an individual perception of his/her competence to successfully perform the desired behaviour (Champion & Skinner, 2008; Jones et al., 2015). HBM research also demonstrated that perceived susceptibility and severity can be combined as perceived threat, which can be measured according to the literature as a single construct (Champion & Skinner, 2008; Jones et al., 2015) or as a second-order construct (Ahadzadeh et al., 2015; Kim & Park, 2012). Perceived threat is defined as the individual and subjective conviction that a health problem is serious and has potential negative consequences (Jones et al., 2015; Kim & Park, 2012). It is directly linked to the concept of self-perception in health (Chan, Pang, Ee, Ding, & Choo, 1998; Vandekar, Knottnerus, Meertens, Dubois, & Kok, 1992), that is related with the fact that perceived rather than the real severity of the complaint is the propelling factor to consult a physician (Vandekar et al., 1992), search for health information on the internet (Ahadzadeh et al., 2015), or use a specific eHealth tool or EHR Portal (Kim & Park, 2012; Nambisan, 2017; Tavares & Oliveira, 2016a), being this a value topic to be addressed within the scope and goals of our study. Figure 2.4 shows the HBM.

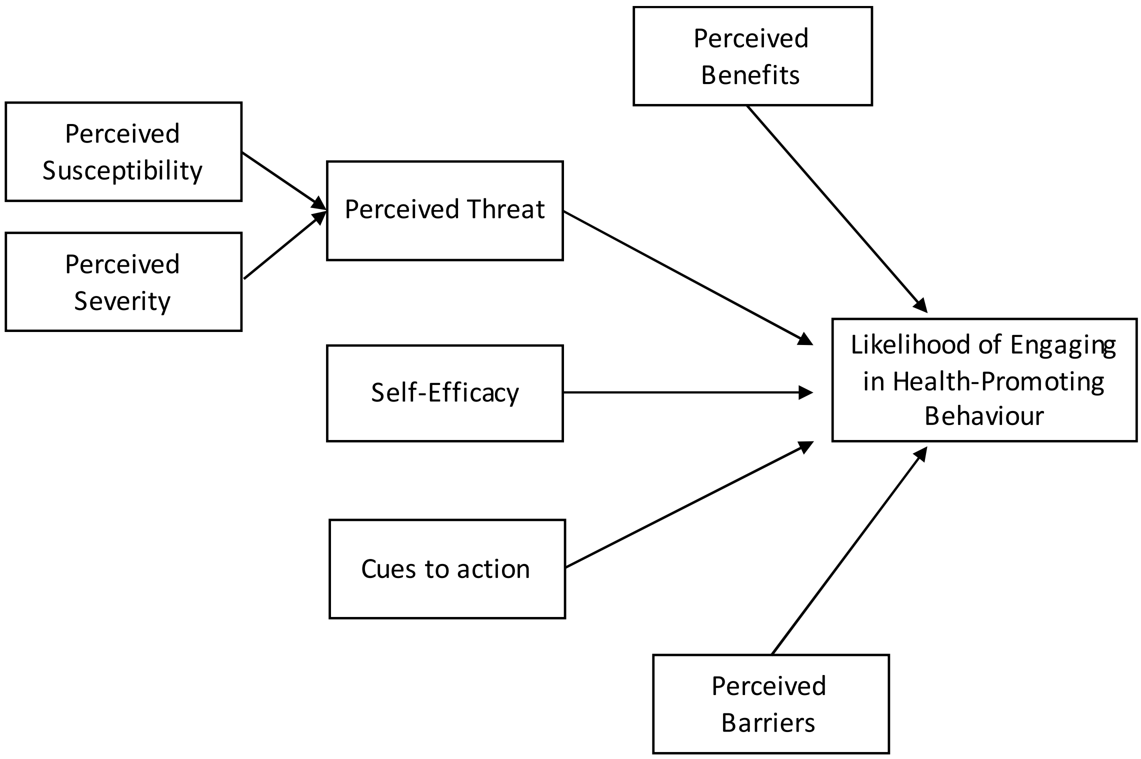


Figure 2.4 HBM Theory (Janz & Becker, 1984; Jones et al., 2015)

DOI Theory

EHR portals is a recent technology still with a low adoption rate. Published studies also identified DOI as a potential theory to explain the adoption of EHR portals (Xiaojun et al., 2014; Zhang et al., 2015). According to DOI Theory, innovation is an idea process or object that is perceived as unknown or new to a particular group of individuals (Rogers, 2003; Zhang et al., 2015). Diffusion is how the information about the innovation flows from one individual to another over time in the social system (Rogers, 2003). There are four key drivers of success of an IT innovation: communication channels, the attributes of the innovation, the social system and the characteristics of the adopters (Rogers, 2003; Zhang et al., 2015). The communication channels are related to the vehicle through which people obtain the information about the innovation, and can be interpersonal communication or mass media (Rogers, 2003; Zhang et al., 2015). According to DOI all members of a social system collaborate at least to the degree of seeking to solve a common problem in order to reach a mutual goal (Rogers, 2003). According to DOI there are different types of adopters: innovators, early adopters, earlier majority, later majority, and laggards (Rogers, 2003). The first two groups of adopters encompass 16% of the members of the social system. They are risk takers and hedgers and usually are well informed about the innovation, knowledgeable about the new technologies, and more economically successful (Rogers, 2003). The next two groups, comprise 68% of the members of the social system, and are earlier and later majority adopters. The last 16% of the members in the social system are named laggards (Rogers, 2003). They are the ones that resist the adoption of an innovation most probably, due to their limited resources and lack of awareness and understanding of the innovation (Rogers, 2003). Particularly relevant for our study are the attributes of an innovation that have been studied in the literature within the scope of our study (Xiaojun et al., 2014; Zhang et al., 2015).

The attributes of an innovation comprise five user-perceived qualities (see Figure 2.5): relative advantage, compatibility, complexity, trialability, and observability (Rogers, 2003). Relative advantage is the extent to which the user perceives improvements or benefits upon the current technology by adopting and using an innovation (Rogers, 2003). Complexity measures the degree to which an innovation is difficult to understand or be used (Rogers, 2003). Compatibility measures the extent to which an innovation is perceived as being consistent with the existing consumer life style values and current and past experiences (Rogers, 2003). Trialability measures the extent to which an innovation may be experimented with on a trialable basis (Rogers, 2003). Observability is the extent to which the results of an innovation are visible to others (Rogers, 2003). Moore and Benbasat (1991) adopted and expanded the original set of innovation characteristics proposed by DOI and developed the constructs to be applicable to the IT setting. Particularly relevant for our study's scope, was the construct observability that was subdivided in results demonstrability and visibility (Moore & Benbasat, 1991). Subsequent studies have found that result demonstrability is more relevant than visibility in predicting user intention to use a technology, and particularly in IT healthcare (Yi et al., 2006).

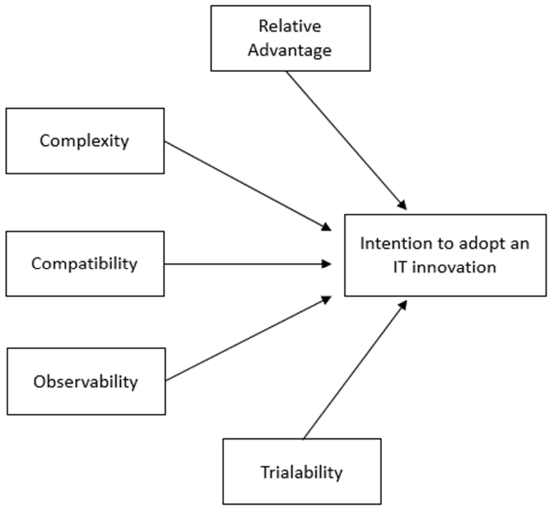


Figure 2.5 DOI Theory innovation attributes and its influence in IT innovation adoption (Martins, Oliveira, & Thomas, 2016; Rogers, 2003)

2.3.5 Future Research and Conclusions

Few studies have been published about the reasons why individuals adopt EHR portals. The complexity of this technology requires specific studies and models that are able to predict the factors that drive the adoption of this new technology. It is consumer-centred, it is a new technology, it is in the healthcare field, and it encompasses a potentially sensitive topic: the patient EHR. The literature review identified four models/theories that may support the understanding of the reasons why healthcare consumers adopt EHR portals: UTAUT2, DOI, HBM, and CFIP. Due to the limited number of studies published to date about the EHR portals, it is reasonable to accept that when developing future research models on the adoption of EHR portals to also use as a reference other studies published with eHealth patient-centred technologies, to help in the theory build up process. Potential differences between countries may also be evaluated. In the following chapters of this dissertation we will go more deeply into each one of these theories, providing empirical testing evidence.

2.4 Literature Review Contributions

Our contribution in this chapter is threefold. Firstly, we provide a definition for the new technology approach to the EHR Portal. Secondly, we review and analyse the body of literature regarding empirical studies that have used quantitative adoption models to study EHR adoption. Thirdly, we provide recommendations for where future studies regarding EHR portals should focus, by identifying key determinant and theories that should be relevant to explain EHR portals adoption.

Chapter 3- Electronic Health Record Portals adoption: Empirical model based on UTAUT2

3.1 Introduction

3.1.1 Overview

Our study focuses on a specific type of eHealth technology, the electronic health record (EHR) portals, which bring clear benefits for both patients and healthcare providers and have received great attention at the governmental level worldwide (Andreassen et al., 2007; Angst & Agarwal, 2009; Tavares & Oliveira, 2016b). 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 (Black et al., 2015; Blumenthal & Tavenner, 2010; Slight et al., 2015). 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 (Tavares & Oliveira, 2016b). EpSOS concentrates on developing a practical eHealth framework and Information and Communication Technology (ICT) infrastructure that will allow secure access to patient health information, including EHR amongst different European countries (Tavares & Oliveira, 2016b).

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.

3.1.2 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 (Allphin, 2012; Ancker et al., 2011; Clamp & Keen, 2007; Knaup & Schoepe, 2014; McDougald Scott et al., 2013; Tavares & Oliveira, 2014a). 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 (Ancker et al., 2011; Angst & Agarwal, 2009; Tavares & Oliveira, 2016b). 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 (Alpay et al., 2010; Andreassen et al., 2007; Tavares & Oliveira, 2014a).

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 (Kern, Edwards, Kaushal, & Investigators, 2015). 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% (Kern et al., 2015). 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 (Angst & Agarwal, 2009), but confidentiality concerns over the use of the information on their EHRs were also reported (Angst & Agarwal, 2009). 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 (Ancker, Brenner, et al., 2015). The overall reduction in privacy concerns by the patients engaging the meaningful use program was 7% (Ancker, Brenner, et al., 2015). After meaningful use stage 1, a stage with great focus on healthcare provider's use of EHR (Blumenthal & Tavenner, 2010; Kern et al., 2015; Tavares & Oliveira, 2016b), new guidelines were issued by the Center for Medicare & Medicaid Services (CMS), called stage 2 meaningful use (Ancker et al., 2011; HealthIT.gov, 2014). 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 (Allphin, 2012; Ancker et al., 2011; HealthIT.gov, 2014). In the US most of the health institutions were not providing access to patients' EHRs via patient portals (Allphin, 2012; Ancker et al., 2011; HealthIT.gov, 2014). 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 (Allphin, 2012; Ancker et al., 2011; HealthIT.gov, 2014; Tavares & Oliveira, 2016b). Recent reports point out that EHR access by the patients is increasing in the US (Slight et al., 2015).

EHR portals have been implemented not only in the US but also in Europe (Tavares & Oliveira, 2016b). 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 (Tavares & Oliveira, 2016b). 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 (Tavares & Oliveira, 2016b). 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 (Tavares & Oliveira, 2016b). 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) (CUF, 2017; Tavares & Oliveira, 2014a, 2016b), 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 (CUF, 2017; Tavares & Oliveira, 2014a, 2016b). 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 (CUF, 2017; Tavares & Oliveira, 2014a, 2016b).

3.1.3 eHealth 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 eHealth technologies and less on the patients' perspective (Angst & Agarwal, 2009; Wilson & Lankton, 2004). 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 3.1.

Most of the research in this area (Jung & Loria, 2010; Lemire, Pare, Sicotte, & Harvey, 2008; Wilson & Lankton, 2004) 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 (2010) to determine the reasons for adoption of eHealth 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 (2004) studied TAM with two different models (motivational model, and integrated model) in order to predict patients' behavioural intention on eHealth services aimed to the patient. Lemire, Pare, et al. (2008) 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 (2012) 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, Bao, and Sorwarb (2017), in which the authors extend TAM to include privacy and trust to study the factors that influence the adoption and use of eHealth 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 (2009) 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, Sicotte, and Pare (2008) to study how patient empowerment may influence the adoption of web based services for the patients.

Table 3.1 summarizes some of the studies made in the area of eHealth 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 3.1 eHealth adoption models

Theory	Dependent variable	Findings	Reference
TAM, motivational model (MM), integrated model (IM)	eHealth behavioural intention	▪ PEOU (TAM), PU (TAM), Intrinsic Motivation (MT) and Extrinsic Motivation (EM) have significant positive influence on behavioural Intention. ▪ IM does not have a better performance than TAM or than MM when predicting behavioural Intention.	(Wilson & Lankton, 2004)
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.	(Angst & Agarwal, 2009)
TAM (qualitative study)	eHealth 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.	(Jung & Loria, 2010)
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.	(Lemire, Pare, et al., 2008)
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.	(Lemire, Sicotte, et al., 2008)
Extended TAM in Health Information Technology (HIT)	HIT behavioural intension	▪ PU, PEOU and perceived threat significantly impacted health consumer's behavioural intention.	(Kim & Park, 2012)
TAM, Trust and Privacy	Intention to adopt eHealth	▪ PEOU, PU and trust are significant predictors.	(Hoque et al., 2017)

Notes:

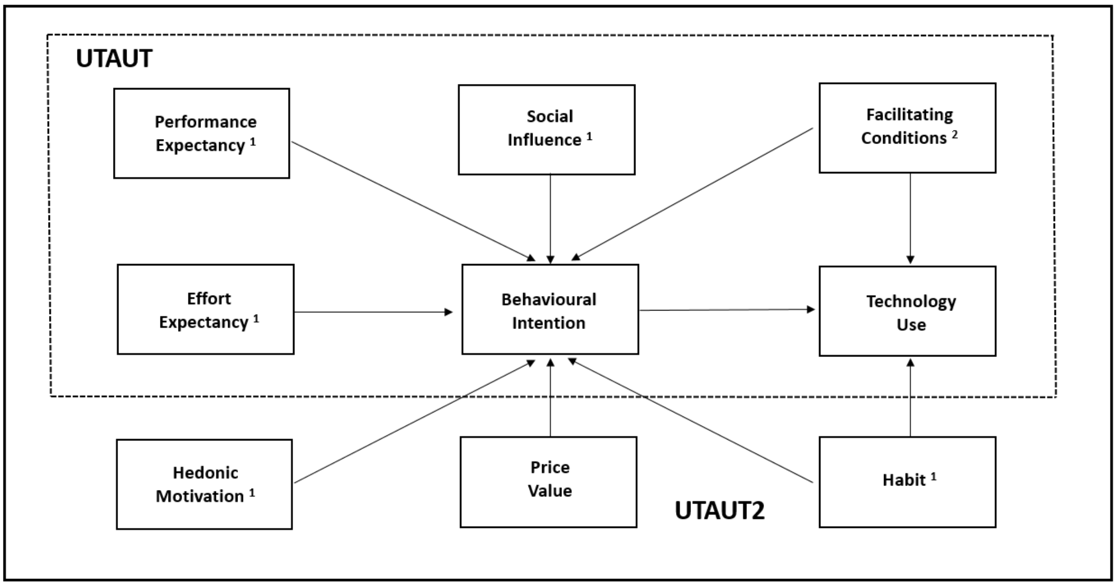
1. EHR: Electronic health record; PEOU: Perceived ease of use; PU: Perceived usefulness; TAM: Technology acceptance model.

3.1.4 Extended Unified Theory of Acceptance and Use of Technology (UTAUT2)

In 2003 Venkatesh et al. (2003) 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 (Venkatesh et al., 2003). Apart from these two constructs from TAM, UTAUT also uses two other constructs, social influence and facilitating conditions (Venkatesh et al., 2003). 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 (Venkatesh et al., 2003). The advantages of UTAUT over TAM and other models have been demonstrated successfully over time (Venkatesh et al., 2012). Although UTAUT provides better results than TAM and other adoption models (Venkatesh et al., 2003; Venkatesh et al., 2012), the focus of UTAUT is the employee technology acceptance at the individual level (Venkatesh et al., 2003; Venkatesh et al., 2012), 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 (Venkatesh et al., 2012). This new model includes the same four UTAUT constructs plus three new constructs that are consumer specific: hedonic motivation, price value, and habit (Venkatesh et al., 2012). 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%) (Venkatesh et al., 2012).

3.1.5 UTAUT2 Research Model

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 3.1). We follow the model proposed by Venkatesh et al. (2012) 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.



Notes: 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 3.1 Research model adapted from Venkatesh et al. (2012)

In our study we followed the same rationale used by Venkatesh et al. (2012) 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. (2012), 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 (Venkatesh et al., 2003; Venkatesh et al., 2012).

Performance expectancy (PU from TAM (Miltgen, Popovič, & Oliveira, 2013)) 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 (Venkatesh et al., 2003).When applied to eHealth 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 (Lemire, Pare, et al., 2008; Wilson & Lankton, 2004).

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 (Venkatesh et al., 2003; Venkatesh et al., 2012).

Effort expectancy (PEOU from TAM (Miltgen et al., 2013)) is associated with how easy it seems to be to use a certain technology (Venkatesh et al., 2003). Earlier research has already pointed out the usability of eHealth (i.e. how easy and simple it is to use an EHR portal) as an important variable (Keselman, Logan, Smith, Leroy, & Zeng-Treitler, 2008; Wilson & Lankton, 2004), 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 (Venkatesh et al., 2003; Venkatesh et al., 2012).

Social influence is the extent to which consumers perceive that others who are important to them, believe they should use a technology (Venkatesh et al., 2003). In the case of eHealth 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 (Lemire, Pare, et al., 2008; Rodrigues et al., 2013).

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 (Venkatesh et al., 2003; Venkatesh et al., 2012).

Facilitating conditions is defined as the individual perception of the support available in order to use a technology (Venkatesh et al., 2003). One of the barriers to consumers' use of health services over the internet is the consumers' resources to access these platforms (Keselman et al., 2008), suggesting that users with better conditions to use eHealth 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 (Venkatesh et al., 2012).

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 (Venkatesh et al., 2003).

Hedonic motivation or perceived enjoyment is defined as the intrinsic motivation of an individual to obtain fun or pleasure from using a technology (Venkatesh et al., 2012). Hedonic motivation is considered to be a strong predictor of behavioural intention (Venkatesh et al., 2012). Earlier research has found that this construct is also important to eHealth consumers and that it could even be a sufficient reason for adoption (Cocosila & Archer, 2010).

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 (Venkatesh et al., 2012).

In UTAUT2 price value is defined as the perceived benefits of using a technology given its costs (Venkatesh et al., 2012). Even though the cost and time savings may influence individuals (Or & Karsh, 2009), the target technology of our study are EHR portals, and most hospitals or health institutions have free internet health services, so the price value may not be significant in behavioural intention (Rodrigues et al., 2013;Tavares & Oliveira, 2014a)

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 (Venkatesh et al., 2012). Habit has proved to be a good predictor of different technologies' adoption, since it is a result of prior experiences (Venkatesh et al., 2012). 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. (Venkatesh et al., 2012)

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 (Venkatesh et al., 2012).

The role of intention as a predictor of usage is critical and has been well-established not only in information systems (IS) in general but also in healthcare and eHealth, with the literature suggesting that the driver of using specific eHealth platforms is preceded by the intention to use them (Kim & Park, 2012; Lai & Wang, 2015; Or & Karsh, 2009; Venkatesh et al., 2003; Venkatesh et al., 2012; Wilson & Lankton, 2004).

H8: Behavioural intention (BI) will have a significant and positive influence on technology use (Venkatesh et al., 2003; Venkatesh et al., 2012).

3.2 Methods

3.2.1 Measurement

All of the items were adopted from Venkatesh et al. (2012), Wilson and Lankton (2004), and Martins et al. (2014), with small modifications in order to adjust to EHR portals technology. The items are shown in Appendix 3.1. 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 (Brislin, 1970; Wild et al., 2005).

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 3.1). 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.

3.2.2 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 (Allphin, 2012; Ancker et al., 2011; Yasnoff & Shortliffe, 2014). 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 (Kalton & Anderson, 1986; Picot et al., 2001). The literature also reports that the users of EHR portals have higher education than the population average (Or & Karsh, 2009; Renahy, Parizot, & Chauvin, 2008; Roblin et al., 2009). A meta-analysis pointed out that the patient factor with the greatest potential impact on the acceptance of consumer health technology was higher education (Or & Karsh, 2009). 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 (Or & Karsh, 2009; Zhang et al., 2015). As a result, we focused our sampling strategy on places where our target population (users of EHR portals) is more prevalent (Kalton & Anderson, 1986; Picot et al., 2001), 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 (Götz, Liehr-Gobbers, & Krafft, 2010; Henseler, Ringle, & Sinkovics, 2009) 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) (Hair et al., 2014). 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 (Hair et al., 2014; Jamil, Wallace, & Abdi, 2009). 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 (Hair et al., 2014; Henseler, et al., 2009), identified as being relevant by the literature to the study topic (Or & Karsh, 2009; Renahy et al., 2008; Roblin et al., 2009). 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 (Hair et al., 2014; Jamil et al., 2009) and use the 386 questionnaires without missing data.

3.2.3 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) (Hair, Ringle, & Sarstedt, 2011). 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 (Henseler et al., 2009). In addition, PLS was applied in both UTAUT and UTAUT2 models (Venkatesh et al., 2003; Venkatesh et al., 2012). We used SmartPLS 2.0.M3 (Ringle, Wende, & Will, 2005), 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.

3.3 Results

3.3.1 Sample Characteristics

Our sample characteristics are shown in Table 3.2.

Table 3.2 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)

3.3.2 Measurement Model

The results of the measurement model are shown in Tables 3.3, 3.4, and 3.5. 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 (Henseler et al., 2009). 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 3.3 reports that all constructs have both CA and CR greater than 0.70, showing evidence of internal consistency (MacKenzie, Podsakoff, & Podsakoff, 2011).

Table 3.3 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
Behavioural 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 ($\sqrt{0.5} \approx 0.7$) (Hair et al., 2014; Henseler et al., 2009; MacKenzie et al., 2011). However, it is recommended to eliminate an item only if its outer standardized loadings are lower than 0.4 (Churchill, 1979; Hair et al., 2014). 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 (Hair et al., 2014) (Table 3.4)

Table 3.4 PLS loadings and cross-loadings

Construct	Item	PE	EE	SI	FC	HM	PV	HT	BI
Performance expectancy (PE)	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 (EE)	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 (SI)	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 (FC)	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 (HM)	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 (PV)	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 (HT)	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
Behavioural intention (BI)	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 (Fornell & Larcker, 1981). As shown in Table 3.3, 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 (Fornell & Larcker, 1981). 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 (Fornell & Larcker, 1981; Henseler et al., 2009). As seen in Table 3.5, 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 (Henseler et al., 2009). We also examined each construct to ascertain that its loadings are greater than all of its cross-loadings (Chin, 1998; Götz et al., 2010). This criterion is also met, as seen in Table 3.4.

Table 3.5 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.

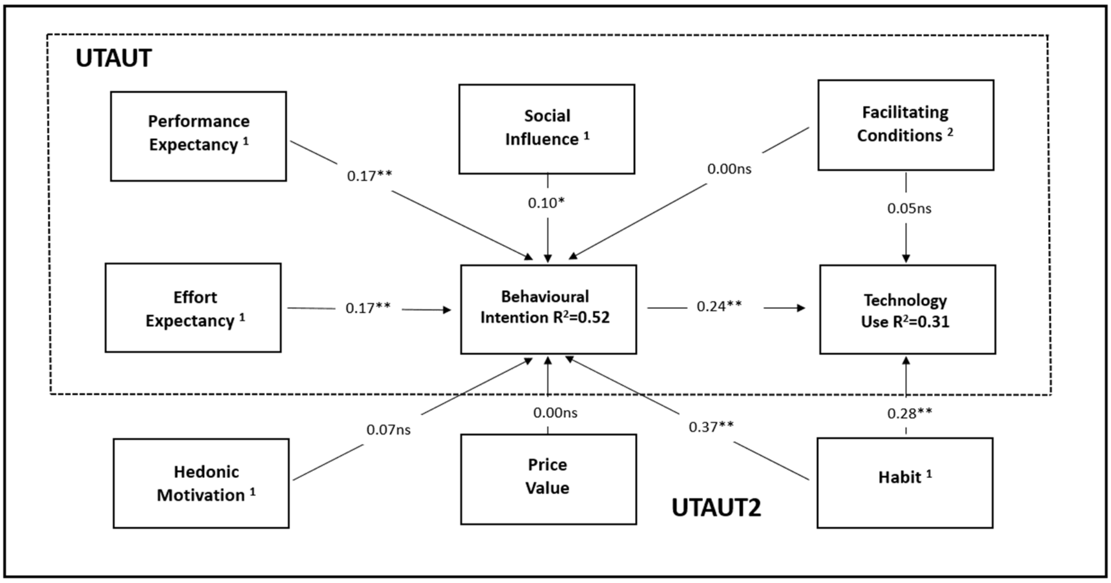
Notes:

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; N.A.: Not applicable.
2. ** $P< 0.01$; * $P< 0.05$
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.

3.3.3 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 3.2 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<0.01; *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 3.2 Structural model results

As Table 3.6 (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*<0.01). 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*<0.01) 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*<0.01). 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 3.6 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. ** $P < 0.01$; * $P < 0.05$

3.4 Discussion

3.4.1 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 3.7 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 (Eurostat, 2014), and almost every individual (95%) had access to the internet in their workplace in 2011 (Eurostat, 2011; Tavares & Oliveira, 2016b). 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 (Peek et al., 2014). 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 (Venkatesh et al., 2012), 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 (Angst & Agarwal, 2009; Hoque et al., 2017; Jung & Loria, 2010; Lemire, Pare, et al., 2008; Lemire, Sicotte, et al., 2008; Wilson & Lankton, 2004), 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 (Or & Karsh, 2009; Renahy et al., 2008; Roblin et al., 2009).

Table 3.7 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; UB: Use; Gender: Gender; Age: Age; HT: Habit.
2. ** $P< 0.01$; * $P< 0.05$; ns = non-significant

3.4.2 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 (Jung & Loria, 2010; Wilson & Lankton, 2004). A very recent study using a TAM extension also found performance expectancy and effort expectancy in the adoption of patient focus eHealth technologies to be important (Hoque et al., 2017). One study adopted a qualitative TAM approach to evaluate patient portals (Jung & Loria, 2010), and the opinion of healthcare consumers in this study was that the design of these platforms should be simple and easy to use (Jung & Loria, 2010). A recent qualitative study that specifically addressed the reasons why the voluntary uptake and use of EHRs have been low (Black et al., 2015), mentioned that the patients wanted a unified view of their medical issues and health management tools (Arsand & Demiris, 2008; Black et al., 2015; Tavares & Oliveira, 2016b). In fact, they want an easier and more effective manner to access their information (Black et al., 2015) 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 (Bjerkan, Hedlund, & Helleso, 2015; Kelders, Pots, Oskam, Bohlmeijer, & van Gemert-Pijnen, 2013). 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 (Lemire, Pare, et al., 2008; Yasnoff & Shortliffe, 2014), digital strategies to promote eHealth 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 (Yasnoff & Shortliffe, 2014). 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 (Black et al., 2015). It was hypothesized in another recent study that the cost of eHealth technologies could influence their adoption by older people, and UTAUT2 might be a good model to test this (Peek et al., 2014). 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 (Yasnoff & Shortliffe, 2014). 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 (Peek et al., 2014; Yasnoff & Shortliffe, 2014).

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 (Black et al., 2015). 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 (Venkatesh et al., 2012). 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.

3.4.3 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 (Allphin, 2012; Ancker et al., 2011; Yasnoff & Shortliffe, 2014). According to the literature, users and early adopters of these types of platforms are younger than the population average and have significantly higher education (Or & Karsh, 2009; Renahy et al., 2008; Roblin et al., 2009). Using a sampling strategy suitable to low prevalence populations (Kalton & Anderson, 1986; Picot et al., 2001), we focused our sampling on education institutions, where our target population is more concentrated (Götz et al., 2010; Hair et al., 2011; Henseler et al., 2009). It is also common to find studies that evaluate eHealth portals addressing the users of a particular portal (Lemire, Sicotte, et al., 2008; Or & Karsh, 2009; Wilson & Lankton, 2004). 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 (Götz et al., 2010; Hair et al., 2011; Henseler et al, 2009).

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 (Lemire, Pare, et al., 2008). 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 eHealth services with a qualitative approach in the case of both health care professionals (Michel-Verkerke & Spil, 2013) and patients (Jung & Loria, 2010), 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 eHealth applied to mobile phones, that is, m-health. Although there are some studies in this field (Handel, 2011; Kharrazi, Chisholm, VanNasdale, & Thompson, 2012; Lim et al., 2011), applying UTAUT2 might yield results of great interest.

3.5 Conclusions

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. (2012) – 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 behavioural 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 (Peek et al., 2014) 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.

Chapter 4- Electronic Health Record Patient Portal Adoption by Health Care Consumers: An Acceptance Model and Survey

4.1. Introduction

4.1.1 Overview

Our study focuses on a specific type of eHealth technology, the patient-accessible electronic health record (EHR) portals (Ancker et al., 2011; Andreassen et al., 2007; Angst & Agarwal, 2009; Tavares & Oliveira, 2014a; Weingart et al., 2006). To better understand the definition of EHR portals it is important to have a clear view of the technologies that support them. First are the patient portals, health care-related online applications that allow patients to interact and communicate with their health care providers (Ancker et al., 2011; Weingart et al., 2006). The second is the EHR, meaning a repository of patient data in digital form, stored and exchanged securely. EHR systems are the software platforms that physician offices and hospitals use to create, store, update, and maintain EHRs for patients (Angst & Agarwal, 2009). By definition, an EHR portal is a Web-based application that combines an EHR system and a Patient Portal, not only for patients to interact with their health care providers, but also to access their own medical records and medical exam results (Allphin, 2012; Ancker et al., 2011; Angst & Agarwal, 2009; Knaup & Schoepe, 2014; Tavares & Oliveira, 2014a; Weingart et al., 2006).

EHR portals may help patients carry out self-management activities, thereby making the use of the health care system more effective and sustainable, not only from the patient care standpoint, but also from a financial perspective due to rising health care costs and budgets in many countries (Alpay et al., 2010; EU Commission, 2004; McKee et al., 2012; Metaxiotis et al., 2004). A recent survey of US health care providers shows that 57% of health care institutions already have a portal in place and 71% value the integration of the EHR system within the patient portal by choosing a product (i.e. patient portal interface) from their EHR vendor (Allphin, 2012). In Europe, not only health care providers, such as hospitals and clinics, provide EHR portals, but also governmental institutions make these platforms available to patients (Alpay et al., 2010; Rodrigues et al., 2013).

This concept of a national-level patient portal progressed into a trans-European initiative, the European Patients Smart Open Services (epSOS). EpSOS concentrates on developing a practical eHealth framework, and an information and communication technology (ICT) infrastructure that enables secure access to patient health information among different European health care systems (epSOS, 2014). The pilot stage of this project, which ended in June 2014, focused on cross-border eHealth services in the following areas: patient summary and cross-border use of electronic prescriptions (epSOS, 2014) . In the United States, a new guidance was issued by the Centers for Medicare & Medicaid Services (CMS) called stage 2 meaningful use (Ancker et al., 2011; HealthIT.gov, 2014). This guidance requires that the eligible professionals and hospitals that participate in the Medicare & Medicaid EHR Incentive Programs must give their patients secure online access to their health information, including EHRs (Allphin, 2012; Ancker et al., 2011; HealthIT.gov, 2014). Stage 2 meaningful use boosted the development of new integrated EHR portals in the United States by health care providers that, according to the new guidance, must not only implement it but also demonstrate effective use by the patients (Allphin, 2012; Ancker et al., 2011; HealthIT.gov, 2014). According to the literature, the most used features in EHR patient portals are as follows: scheduling medical appointments, email messaging, requesting prescription refills, and checking of patients' medical exams (Andreassen et al., 2007; Irwin, 2014; Weingart et al., 2006).

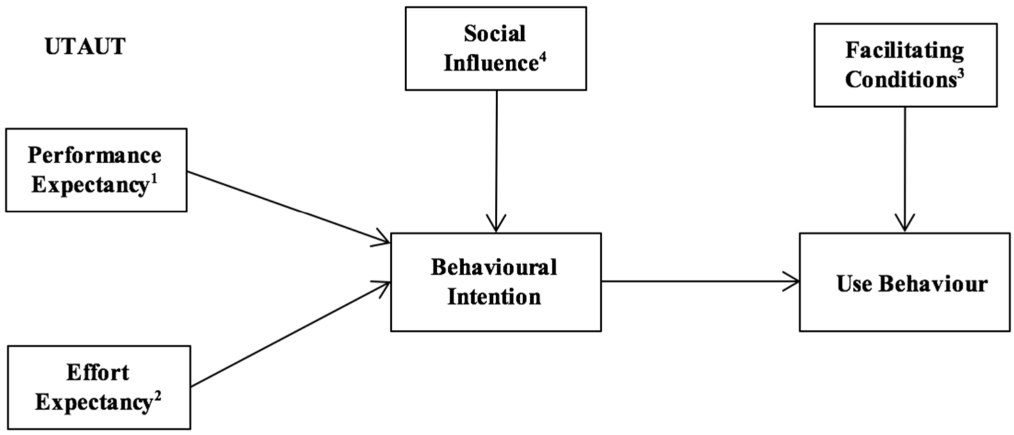
The aim of this study is to identify a set of determinants in the adoption of electronic EHR portals by health care consumers. In our study, we examine these determinants in the field of eHealth technology use and acceptance by health care consumers. We then propose a new research model based on the Extended Unified Theory of Acceptance and Use of Technology in a consumer context (UTAUT2) by integrating a new construct from the health care area, self-perception (SP), and a new moderator, chronic disability (CD) (Angst & Agarwal, 2009; Lemire, Sicotte, et al., 2008; Millard & Fintak, 2002; Venkatesh et al., 2012).

In this paper, we first review the literature concerning information technology (IT) adoption models regarding consumer health care. We then present a research model to analyse EHR portals for the health care consumer. Finally, we discuss the issue and present conclusions.

4.1.2 Theoretical Background

There have been several theoretical models developed from theories in psychology, sociology, and consumer behaviour employed to explain technology acceptance and use (Venkatesh et al., 2012). The goal of this study is to focus specifically on EHR portal adoption from the perspective of the health care consumer, so it is of the utmost importance to review the literature in this particular field. Adoption of eHealth technologies by patients is clearly a very important topic in information systems (IS) in health care. The adoption of eHealth technologies by health care consumers still requires more attention and research due to the limited number of studies reported in the literature to date (Angst & Agarwal, 2009; Lai & Wang, 2015; Or & Karsh, 2009; Peek et al., 2014; Thackeray, Crookston, & West, 2013). The use of the UTAUT2 model might be beneficial to eHealth adoption due to its consumer-specific constructs like price value (Peek et al., 2014).

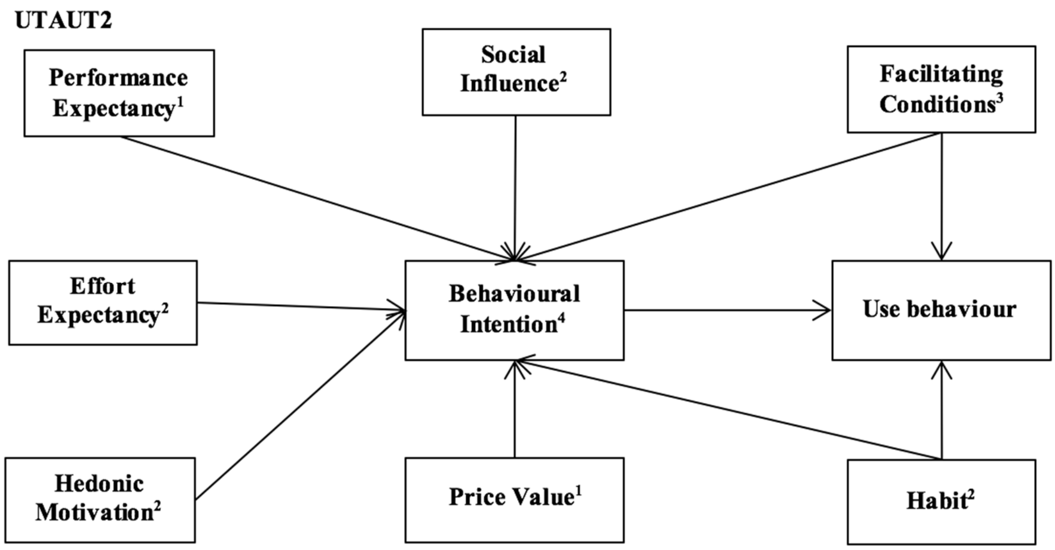
When studying eHealth and health care adoption by health care professionals, the most common adoption models used are the Technology Acceptance Model (TAM) (Dunnebeil et al., 2012; Ketikidis et al., 2012) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Chang et al., 2007; Maillet et al., 2015; Vanneste et al., 2013; Vinko, Brecelj, Erzen, & Dinevski, 2013; Yi et al., 2006). Evaluating the studies published in the field of consumer health IT adoption, and more specifically in the use and adoption of eHealth tools by the health care consumer, most studies use TAM or extensions of TAM (Ahadzadeh et al., 2015; Kim & Park, 2012; Nasir & Yurder, 2015; Or & Karsh, 2009; Wilson & Lankton, 2004; Wong, Yeung, Ho, Tse, & Lam, 2014). TAM was designed and tailored in IS contexts to predict information technology acceptance and usage on the job. TAM uses three dimensions: perceived usefulness (PU), that is "the degree to which a person believes that using a particular system would enhance his or her job"; perceived ease of use (PEOU), that is "the degree to which a person believes that using a particular system would be free of effort"; and attitude toward technology use (Ahadzadeh et al., 2015; Davis, 1989; Venkatesh et al., 2003). PU and PEOU together affect the attitude toward technology use, which in turn influences behavioural intention to adopt (Ahadzadeh et al., 2015; Davis, 1989). UTAUT formulates a unified model that integrates elements of eight models in the field of IT acceptance, including from TAM, which incorporates the concept of PU as performance expectancy and PEOU as effort expectancy (Venkatesh et al., 2003). Apart from these two constructs from TAM, UTAUT also uses two other constructs, social influence (SI) and facilitating conditions (FC). All of these are joined together in the model along with four moderators—age, gender, experience, and voluntariness of use. The model and its relationships are illustrated in Figure 4.1 (Venkatesh et al., 2003). The R^2 obtained with UTAUT was superior to those of any of the individual models, including TAM, making a synthesis of the different theories by bringing together into the model the constructs that have a significant impact (Venkatesh et al., 2003; Venkatesh et al., 2012). For example, with UTAUT it is possible to measure the impact of social influence on behavioural intention, something that was not measured with TAM (Venkatesh et al., 2003; Venkatesh et al., 2012). Although UTAUT provides better results than TAM and other IS adoption models, the focus of UTAUT is also the employee technology acceptance at the individual level, which is not the focus of our paper because our target group is health care consumers (Venkatesh et al., 2012).



Notes: 1. Moderated by age and gender; 2. Moderated by age, gender and experience; 3. Moderated by age and experience; 4. Moderated by age, gender, experience and voluntariness of use.

Figure 4.1 Unified Theory of Acceptance and Use of Technology (UTAUT) model adapted from Venkatesh et al. (2003)

Ideally, we need a model tailored to the consumer use context, and in this specific field, UTAUT2 was developed with this goal, obtaining very good results (Peek et al., 2014; Venkatesh et al., 2012). This new model includes the same four UTAUT constructs, but which are moderated differently. The constructs are now moderated only by age, gender, and experience (Venkatesh et al., 2012). The moderator voluntariness of use was dropped since the target population was not obliged to use the technology (Venkatesh et al., 2012). UTAUT2 also introduces three new constructs (i.e. specific consumer adoption constructs): hedonic motivation, price value, and habit. Hedonic motivation and price value explain behavioural intention, while habit explains behavioural intention and use behaviour (Venkatesh et al., 2012). Compared to UTAUT, the extensions proposed in UTAUT2 that are consumer specific produced a substantial improvement in the variance explained in behavioural intention (from 56% to 74%) and technology use (from 40% to 52%) (Venkatesh et al., 2012). Including these three new constructs made UTAUT2 a more suitable model for consumer-centred technologies (Venkatesh et al., 2012). Figure 4.2 explains the UTAUT2 model. The definitions of the different constructs used in the UTAUT and UTAUT2 models are provided in the research model section of this paper. Most of the existing UTAUT2 literature focuses on other types of technologies, such as online purchasing, mobile banking, and Web-based services (Baptista & Oliveira, 2015; Lian, 2015; Pascual-Miguel, Agudo-Peregrina, & Chaparro-Pelaez, 2015; Venkatesh et al., 2012). A recently published study used UTAUT2 in health and fitness apps, which is not exactly the same technology scope and type of eHealth service as EHR portals, but obtained the following results: performance expectancy, hedonic motivation, price value, and habit were significant predictors of intention of continued usage (Yuan, Ma, Kanthawala, & Peng, 2015).



Notes: 1. Moderated by age and gender; 2. moderated by age, gender, and experience; 3. Effect on behavioural intention is moderated by age, gender, and experience. Effect on use behaviour is moderated by age and experience; 4. Moderated by experience.

Figure 4.2 Extended Unified Theory of Acceptance and Use of Technology in a consumer context (UTAUT2) model adapted from Venkatesh et al. (2012)

Table 4.1 summarizes some of the studies performed in the area of eHealth, the theory or theories behind the studies, the dependent variable that is being explained by each study, and the most important findings. The target population in all studies was patients and the technologies have similarities with EHR portals (Angst & Agarwal, 2009; Jung & Loria, 2010; Kim & Park, 2012; Lemire, Pare, et al., 2008; Lemire, Sicotte, et al., 2008; Wilson & Lankton, 2004).

Table 4.1 eHealth adoption models

Theory	**Dependent variable**	**Findings**	**Reference**
TAM, motivational model (MM), integrated model (IM)	eHealth behavioural intention	▪ Users' perceived ease of use (PEOU), users' perceived technology usefulness (PU), intrinsic motivation (MT), and extrinsic motivation (EM) have a significant positive influence on behavioural Intention. ▪ IM does not have a better performance than TAM or MM when predicting behavioural Intention.	(Wilson & Lankton, 2004)
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.	(Angst & Agarwal, 2009)
TAM (qualitative study)	eHealth 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.	(Jung & Loria, 2010)
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 to use behaviour.	(Lemire, Pare, et al., 2008)
Personal empowerment	Internet use behaviour as a source of information	▪ There are three types of attitudes encouraging Internet use to seek health information: professional, consumer, and community logic.	(Lemire, Sicotte, et al., 2008)
Extended TAM in health information technology (HIT)	HIT behavioural intention	▪ PU, PEOU, and perceived threat significantly impacted health consumers' behavioural intention.	(Kim & Park, 2012)

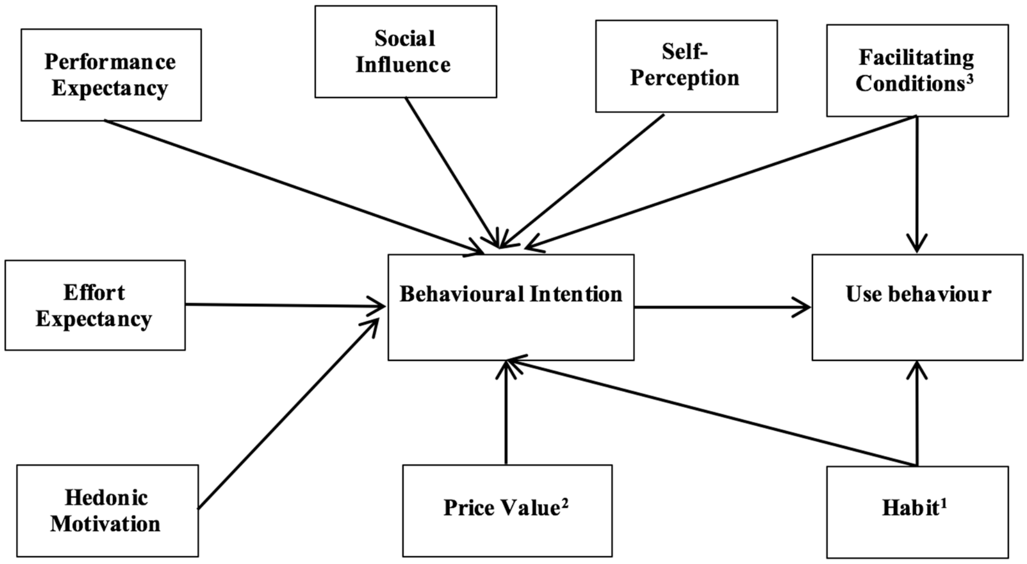
Notes:

1. TAM: Technology adoption model; EHR: Electronic health record

4.1.3 Research Model

UTAUT2 was developed as an adoption model providing the general factors of IT adoption in consumer use. However, according to Venkatesh et al. (2012), in certain situations in which the technology may be influenced by specific factors it may be necessary to extend the model with new constructs, moderators, and relationships. We therefore identified key additional constructs and relationships based on the literature review that are specific to IT health care adoption to be integrated into UTAUT2, thus tailoring it to the eHealth consumer context, with the special aim of studying the adoption of EHR portals. We did this by (1) identifying a key construct from earlier research in health care—self-perception—and by (2) adding a new moderator specific to health care use—chronic disability (see Figure 4.3).

Published studies suggest that patients with chronic illness, severe illness, or disability are more likely to use eHealth technologies if they have the resources and support available (Fox, 2007; Millard & Fintak, 2002; Renahy et al., 2008). A national survey in the United States shows that 86% of people living with disability or chronic illness with Internet access have looked online for information about health topics, compared with 79% of Internet users with no chronic conditions (Fox, 2007). A recent study using a TAM extended version with the health belief model measured the perceived health risk to chronic diseases (Ahadzadeh et al., 2015). Using chronic disability with UTAUT2 in the field of EHR portals is not only a new approach, but also one that takes advantage of the existence of the construct facilitating conditions—defined as the individual perception of the support available for using a technology activity (Venkatesh et al., 2003)—that can be moderated by chronic disability, something that can be more properly tested with UTAUT2 than with TAM (Venkatesh et al., 2012). Recent studies tackled the need to study the variables that can drive the patients to be more active in their own health management (Alpay et al., 2010; Peek et al., 2014). Self-perception in health (Chan et al., 1998; Kaleta, Polanska, Dziankowska-Zaborszczyk, Hanke, & Drygas, 2009; Vandekar et al., 1992), called the self-perception construct, considers that the perceived, rather than the real, severity of the health complaint could be the propelling force behind the action in health care (Kaleta et al., 2009; Menec, Chipperfield, & Perry, 1999; Vandekar et al., 1992). EHR portals are interfaces that links patients with health care professionals, and this construct is relevant to understanding if the patient's awareness about her/his own health status can be a driver to adopt EHR portals. Other studies using the health belief model with TAM (Ahadzadeh et al., 2015; Kim & Park, 2012) incorporated other constructs related to the health belief model concept. One such study was by Kim and Park (2012), who studied health-related constructs like health belief and concerns or perceived health status, conceptually similar to self-perception, that have been shown to have an indirect effect on the behavioural intention to use health information technology (Kim & Park, 2012). This shows the importance of measuring this dimension in our study with a consumer-centred adoption model.



Notes: 1. Moderated by age or gender; 2. Moderated by age; 3. Moderated by chronic disability on use

Figure 4.3 Illustrates the new research model

Performance expectancy is defined as the degree to which using a technology will provide benefits to consumers in carrying out certain activities (Martins et al., 2014; Venkatesh et al., 2003). Our literature review indicates that health care consumers tend more to adopt eHealth technologies that provide clear benefits, such as obtaining an electronic medical prescription via EHR portals (Alpay et al., 2010; Arsand & Demiris, 2008; Keselman et al., 2008).

Hypothesis 1 (H1) states that performance expectancy will positively influence behavioural intention.

Effort expectancy is the degree of ease related to consumers' use of technology (Venkatesh et al., 2003). The easier it is for consumers to understand and use an eHealth technology, the greater is the probability that they will adopt it (Alpay et al., 2010; Keselman et al., 2008).

Hypothesis 2 (H2) states that effort expectancy will positively influence behavioural intention.

Social influence is the extent to which consumers perceive that others who are important to them (e.g. friends and family) believe they should use a particular technology (Venkatesh et al., 2012). In the case of eHealth, this can also be an important construct since people who share the same diseases (e.g. multiple sclerosis) or the same health condition (e.g. obesity) tend to be influenced by others having the same condition (Fisher & Clayton, 2012; Thackeray et al., 2013).

Hypothesis 3 (H3) states that social influence will positively influence behavioural intention.

The construct, facilitating conditions, is defined as the individual perception of the support available for using a technology activity (Venkatesh et al., 2003). One of the barriers to consumers' use of health services over the Internet is the consumers' lack of resources to access these platforms (Keselman et al., 2008), suggesting that users with better conditions to use eHealth technologies favour EHR portals adoption.

Hypothesis 4 (a) (H4 [a]) states that facilitating conditions will positively influence behavioural intention.

Chronic disability is an incapacitating situation (e.g. chronic illness) that affects a patient permanently or for long-term periods. Our literature review reveals that patients with chronic illness or disability are more likely to use eHealth technologies if they have the resources and support available (i.e. facilitating conditions) (Millard & Fintak, 2002; Thackeray et al., 2013).

Hypothesis 4 (b) (H4 [b]) states that chronic disability will moderate the effect of facilitating conditions on use behaviour, such that the effect will be stronger for chronically disabled people.

Hedonic motivation is defined as intrinsic motivation (e.g. enjoyment) and has been included as a key predictor in much of the reported consumer behaviour research (Venkatesh et al., 2012). Obtaining and dealing with information about our health status by using eHealth technologies may be an enjoyable process, or in some cases may not be when a patient has, for example, an incurable disease (Lee et al., 2010). Nevertheless, in a recent study with UTAUT2 in eHealth, hedonic motivation was found to have a significant impact on behavioural intention (Yuan et al., 2015). We then propose that this specific construct may have a significant impact in predicting EHR Portal use.

Hypothesis 5 (H5) states that hedonic motivation will have a positive influence on behavioural intention.

Price value in a consumer use environment is also a relevant factor as, unlike workplace technologies, consumers must bear the costs related with the purchase of devices and services (Venkatesh et al., 2012). If a patient can obtain her/his medical prescription via an EHR portal, she/he can save transportation costs by avoiding a trip to a health centre or hospital. The better the perception a health care consumer has about the *price value* of an eHealth technology (i.e. that it can help save money), the more likely it is that she/he will adopt it (Alpay et al., 2010; Metaxiotis et al., 2004); older people tend to give more importance to price in eHealth (Peek et al., 2014).

Hypothesis 6 (H6) states that age will moderate the effect of price value on behavioural intention, such that the effect will be stronger for older people.

Habit can be defined as the extent to which people tend to execute behaviours automatically because of learning (Venkatesh et al., 2012). We can expect that habit will positively influence eHealth adoption, as it does in other IT adoption fields, since habit is a concept that should not be specific to an IT technology (Venkatesh et al., 2012). The literature review indicates that in eHealth, younger people and women tend to have the habit to use more eHealth technologies (Millard & Fintak, 2002; Thackeray et al., 2013).

Hypothesis 7 (a1) (H7 [a1]) states that age will moderate the effect of habit on behavioural intention, such that the effect will be stronger for younger people.

Hypothesis 7 (a2) (H7 [a2]) states that gender will moderate the effect of habit on behavioural intention, such that the effect will be stronger for women.

Hypothesis 7 (b1) (H7 [b1]) states that age will moderate the effect of habit on use behaviour, such that the effect will be stronger for younger people.

Hypothesis 7 (b2) (H7 [b2]) states that gender will moderate the effect of habit on use behaviour, such that the effect will be stronger for women.

Behind the concept, self-perception, is the health belief model. The model assumes that subjective health considerations determine whether people perform a health-related action, such as consulting their physician (Vandekar et al., 1992). For example, the health belief model considers the perceived, rather than the real, severity of the complaint to be the propelling force behind the action (Vandekar et al., 1992).

Studies about patients that look for information online seem to confirm the concept of the health belief model; the results show that a larger proportion of respondents who described their health as poor indicated that they looked for health-related information online "often" compared with those who described their health as fair or better (Millard & Fintak, 2002). We therefore add self-perception as a predictor of health consumer behavioural intention to use a technology.

Hypothesis 8 (H8) states that self-perception will positively influence behavioural intention.

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 health care and eHealth, with the literature suggesting that the driver of using specific eHealth platforms is preceded by the intention to use them (Kim & Park, 2012; Lai & Wang, 2015; Vandekar et al., 1992; Venkatesh et al., 2003; Venkatesh et al., 2012; Wilson & Lankton, 2004)

Hypothesis 9 (H9) states that behavioural intention will positively influence use behaviour.

4.2 Methods

4.2.1 Measurement

All of the items were adopted from Venkatesh et al. (2012), Wilson and Lankton (2004), and Vandekar et al. (1992) with small modifications in order to adjust to EHR Portal technology. The items are shown in Appendix 4.1. The questionnaire was administered in Portuguese through a Web hosting service after being translated by a professional translator. 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 a professional translator, and compared to the original (Brislin, 1970).

The scales' items were measured on a 7-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 Portal 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), with women represented by 0. Chronic disability was coded as a dummy variable (0 or 1), with its absence represented by 0.

Before the respondents could see any of the questions, an introduction was made explaining the concept of EHR portals (see Appendix 4.1). 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.

4.2.2 Data Collection

A pilot survey was conducted to validate the questions and the scale of the survey. From the pilot survey, we had 30 responses demonstrating that all of the items were reliable and valid. The data from the pilot survey were not included in the main survey.

According to the literature, the technology that we are studying (EHR portals) is being used by less than 7% of the total number of health care consumers or patients (Allphin, 2012; Ancker et al., 2011; Yasnoff & Shortliffe, 2014). We are therefore sampling a group of people that could be defined as a rare population, as it constitutes a small proportion of the total population, and specific sample strategies can be used that are suitable in this case (Kalton & Anderson, 1986; Picot et al., 2001). We have a disproportionate stratification of our target population compared with the general population, because according to the literature, users and early adopters of these types of platforms have significantly higher education (Or & Karsh, 2009; Renahy et al., 2008; Roblin et al., 2009). As a result, we focused our sampling strategy in places where our target population—users of EHR portals—are more concentrated (Kalton & Anderson, 1986; Picot et al., 2001); thus, we selected educational institutions.

The survey, via hyperlink, was sent by email in October 2013 to a total of 1618 people at three institutions that provide educational services, from which we obtained 350 responses. NOVA Information Management School (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, and the anonymity of the information collected. A reminder was sent 2 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 465 respondents out of 1618 (28.74% response rate). After removing the invalid responses, the final sample consisted of 360 respondents. A questionnaire was considered invalid if not all questions were answered. According to our statistical modelling method, we cannot use incomplete questionnaires (Götz et al., 2010; Henseler et al., 2009).

4.2.3 Data Analysis

To test the research model, we used the partial least squares (PLS) method, which is a causal modelling approach that represents a variance-based technique of path modelling (Henseler et al., 2009). Our main reasons for choosing this method were the complexity of the model (i.e. many moderators) and the fact that the PLS method is oriented to explain variance of the research model and to identify key constructs (Götz et al., 2010; Hair et al., 2011; Henseler et al., 2009). We used the software program SmartPLS version 2.0.M3 (SmartPLS GmbH) (Ringle et al., 2005) 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.

4.3 Results

4.3.1 Sample Characteristics

Our sample characteristics are shown in Table 4.2

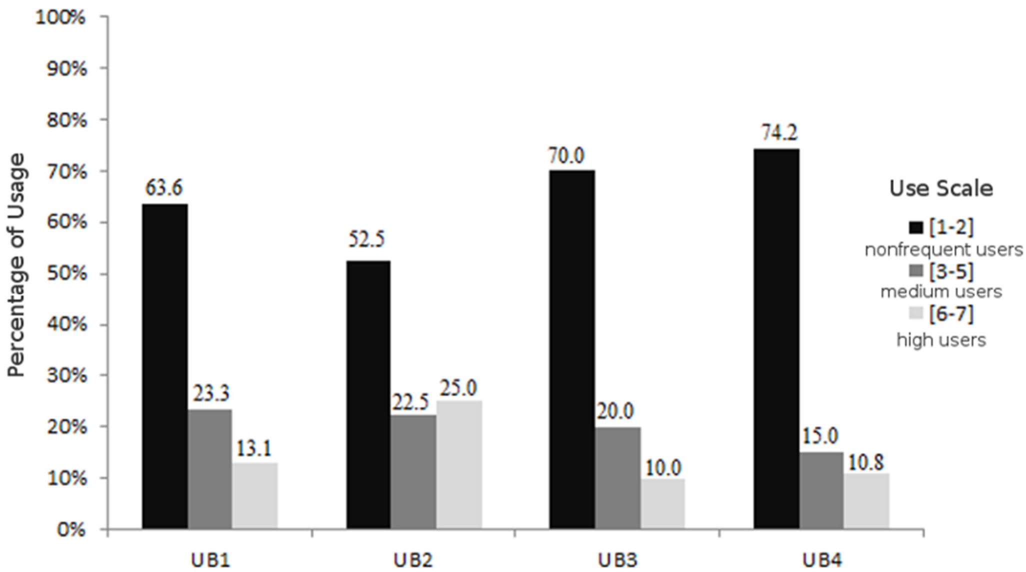
Table 4.2 Sample characteristics (n=360)

Variable	Category	Frequency (%)
Age (in years)	18-20	69 (19.2)
	20-24	75 (20.8)
	25-30	76 (21.1)
	30-40	89 (24.7)
	>40	51 (14.2)
Gender	Male	142 (39.4)
	Female	218 (60.6)
Chronic illness/disability	No	308 (85.6)
	Yes	52 (14.4)
Education	Undergraduate	132 (36.7)
	Bachelor’s degree	87 (24.2)
	Postgraduate	70 (19.4)
	Master Degree or more	71 (19.7)

The literature mentions that users of EHR portals are younger than the population average and have significantly higher education (Or & Karsh, 2009; Renahy et al., 2008; Roblin et al., 2009); the results shown in Table 4.2 are aligned with the literature findings.

4.3.2 Usage Results

Use was measured on a scale that ranges from *never* (1) to *every time I need* (7). In Figure 4.4, we grouped the results by nonfrequent users of a particular EHR Portal feature (scale from 1 to 2), medium users (scale from 3 to 5), and high users (scale from 6 to 7). These results show that the fact that people know about the technology and enter and register in these portals does not make them frequent users. Our study results are aligned with those of earlier studies and reports (Millard & Fintak, 2002; Rodrigues et al., 2013; Weingart et al., 2006); also, the results from our study show that only 30% of users use a portal regularly to check their EHR. Medical appointment scheduling is the feature with the highest usage.



Notes: UB: use behaviour; UB1: management of personal information and communication with health providers; UB2: medical appointment schedule; UB3: check their own EHR; UB4: request for medical prescription renewals.

Figure 4.4 Types of usage patterns of electronic health record (EHR) portals

4.3.3 Measurement Model

The results of the measurement model are shown in Tables 4.3, 4.4, and 4.5 and in Appendix 4.2. To evaluate construct reliability, one can use Cronbach alpha or the composite reliability coefficient (CR). Although Cronbach alpha is more often used, CR is more appropriate for PLS since it prioritizes indicators according to their individual reliability and takes into account that indicators have different loadings, unlike Cronbach alpha (Hair et al., 2014). Table 4.3 reports that all constructs have a CR greater than 0.70, showing evidence of internal consistency (Henseler et al., 2009; MacKenzie et al., 2011).

Table 4.3 Cronbach alpha, composite reliability, and average variance extracted

Construct	**Cronbach alpha**	**Composite reliability coefficient (CR)**	**Average variance extracted (AVE)**
Performance expectancy	0.90	0.94	0.83
Effort expectancy	0.91	0.94	0.79
Social influence	0.98	0.98	0.96
Facilitating conditions	0.80	0.87	0.63
Hedonic motivation	0.93	0.96	0.88
Price value	0.93	0.96	0.88
Habit	0.74	0.85	0.66
Self-perception	0.67	0.81	0.52
Behavioural intention	0.90	0.94	0.83

In order to have good indicator reliability, it is desired that the latent variable explain more than half of the indicators' variances. The correlation between the constructs and their indicators should ideally be greater than 0.70 ($\sqrt{0.50} \approx 0.70$) (Henseler et al., 2009; MacKenzie et al., 2011). However, an item is recommended to be eliminated only if its outer standardized loadings are lower than 0.40 (Churchill, 1979). The measurement model has issues with two indicators' reliabilities—SP3 and SP5—which were removed; FC4, SP4, and SP6 are lower than 0.70, but still greater than 0.40 (see Appendix 4.2).

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 (Fornell & Larcker, 1981; Hair et al., 2014). As shown in Table 4.3, all of the indicators respect this criterion. Finally, discriminant validity can be evaluated with the Fornell-Larcker criterion (Fornell & Larcker, 1981). 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 (Fornell & Larcker, 1981;

Henseler et al., 2009). As seen in Table 4.4, all diagonal—square root of AVEs—are greater than the correlation between constructs—off-diagonal elements. In addition, another criterion can be assessed, although it is a more liberal one (Henseler et al., 2009). For each construct, we also examined if loadings are greater than all of its cross-loadings (Chin, 1998; Götz et al., 2010). This criterion is also met, as seen in Appendix 4.2.

Table 4.4 Correlations and square root of average variance extracted

	PE	EE	SI	FC	HM	PV	HT	SP	BI	UB	Age	Gender	CD
PE	**0.91**												
EE	0.47	**0.89**											
SI	0.31	0.24	**0.98**										
FC	0.25	0.57	0.23	**0.79**									
HM	0.47	0.44	0.31	0.32	**0.94**								
PV	0.42	0.33	0.34	0.26	0.42	**0.94**							
HT	0.43	0.29	0.55	0.26	0.48	0.46	**0.81**						
SP	0.04	-0.08	0.15	-0.06	0.08	0.08	0.16	**0.72**					
BI	0.50	0.43	0.43	0.29	0.44	0.35	0.61	0.17	**0.91**				
UB	0.23	0.18	0.39	0.24	0.17	0.23	0.41	0.10	0.44	N/A			
Age	-0.01	-0.04	0.13	-0.03	-0.01	0.08	0.09	0.08	0.08	0.20	N/A		
Gender	-0.02	-0.04	0.05	0.00	-0.08	0.05	0.00	0.05	-0.03	0.00	0.11	N/A	
CD	-0.08	-0.10	0.02	-0.08	-0.06	-0.02	0.03	0.24	0.01	0.13	0.18	0.09	N/A

Notes:

1. Off-diagonal elements are correlations;
2. Diagonal elements are square roots of average variance extracted;
3. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; FC: Facilitating conditions; HM: Hedonic motivation; PV: Price value; HT: Habit; SP: Self-perception; BI: Behavioural intention; UB: Use behaviour; CD: Chronic disability; N/A: not applicable, because they are not reflective constructs.

Use, which was modelled using four formative indicators, is evaluated by specific quality criteria related to formative indicators. As seen in Table 4.5, the variance inflation factors are all below 5, suggesting that multi-collinearity is not an issue (Hair et al., 2014). In addition, the indicators comply with the criterion of being statistically significant or, if not significant, its outer loading must be higher than 0.50 (Hair et al., 2014).

Table 4.5 Formative indicators' quality criteria

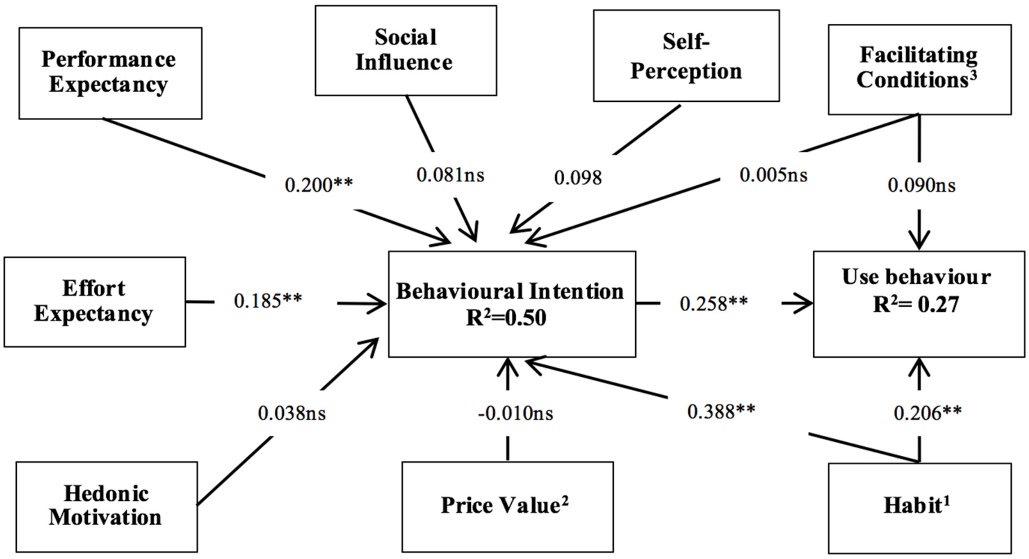
Indicators	VIF[a]	Weights	*t* (weights)	Outer loadings	*t* (loadings)
UB1[b]	2.61	0.86	4.70**	0.95	21.08**
UB2	1.71	0.35	2.27*	0.75	8.41**
UB3	3.24	0.12	0.57	0.74	8.46**
UB4	2.47	-0.33	1.66	0.54	4.50**

Notes:
1. VIF: variance inflation factor
2. *P< 0.05; **P<0.01
3. UB1: management of personal information and communication with health providers; UB2: medical appointment schedule; UB3: check their own EHR; UB4: request for medical prescription renewals.

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

4.3.4 Structural Model

The structural model path significance levels were estimated using a bootstrap with 5000 iterations of resampling to obtain the highest possible consistency in the results. The R^2 was used to evaluate the structural model. Overall, the model explains 49.7% and 26.8% of the variance in behavioural intention and use behaviour, respectively (see Figure 4.5).



Notes: 1. Moderated by age or gender; 2. Moderated by age; 3. Moderated by chronic disability on use; *P<0.05; **P<0.01; ns: nonsignificant.

Figure 4.5 Structural model results

Table 4.6 presents a summary of all the hypotheses tested and their support (or not) based on statistical tests. As Table 4.6 shows, the predictors of behavioural intention are performance expectancy ($\hat{\beta}$=0.200; P<0.01), effort expectancy ($\hat{\beta}$=0.185; P< 0.01), habit ($\hat{\beta}$=0.388; P<0.01), and self-perception ($\hat{\beta}$= 0.098; P< 0.05). The predictors of technology use behaviour are habit ($\hat{\beta}$=0.206; P<0.01) and behavioural intention ($\hat{\beta}$=0.258; P<0.01). Age also has a positive and significant effect on use behaviour. This finding suggests that older individuals use EHR portal technologies more than do younger individuals.

Table 4.6 Summary of findings regarding hypotheses

Dependent variables	Independent variables	Hypotheses (H)	Beta	*T*	R^2
Behavioural intention					49.7%
	PE	H1 (supported)	0.200	3.619**	
	EE	H2 (supported)	0.185	2.907**	
	SI	H3 (not supported)	0.081	1.544	
	FC	H4 (a) (not supported)	0.005	0.112	
	HM	H5 (not supported)	0.038	0.678	
	PV	N/A	-0.010	0.203	
	PV x age	H6 (not supported)	0.026	0.563	
	HT	N/A	0.388	7.320**	
	HT x age	H7 (a1) (not supported)	0.033	0.584	
	HT x gender	H7 (a2) (not supported)	0.010	0.183	
	SP	H8 (supported)	0.098	2.285*	
	Age	N/A	0.065	1.408	
	Gender	N/A	0.052	0.454	
	Gender x age	N/A	-0.087	0.078	
	CD	N/A	-0.002	0.049	
Use behaviour					26.8%
	FC		0.090	1.755	
	FC x CD	H4 (b) (not supported)	0.076	0.391	
	HT	N/A	0.206	2.752**	
	HT x age	H7 (b1) (not supported)	0.060	0.621	
	HT x gender	H7 (b2) (not supported)	0.066	0.704	
	BI	H9 (supported)	0.258	4.036**	
	Age	N/A	0.170	2.387*	
	Gender	N/A	-0.013	0.092	
	Gender x age	N/A	0.005	0.031	
	CD	N/A	-0.081	0.476	

Notes:

1. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; FC: Facilitating conditions; HM: Hedonic motivation; PV: Price value; HT: habit; SP: Self-perception; CD: Chronic disability; BI: Behavioural intention; N/A: not applicable
2. *P<0.05; **P<0.01.

We also tested the mediating role of behavioural intention between the independent variables and use behaviour (see Table 4.7). To test if behavioural intention mediated the independent variables on use behaviour, we followed the Preacher and Hayes (Hair et al., 2014) approach. Initially, we check if only direct effects—without mediator (i.e. behavioural intention)—are statistically significant in explaining use behaviour. Based on this (Step 1) we concluded that habit, facilitating conditions, and social influence are statistically significant, meaning that any of these factors might mediate behavioural intention. Then in Step 2, we include the mediator variable (i.e.

behavioural intention) in order to test if indirect effect of habit, facilitating conditions, or social influence are significant on use behaviour. Only the indirect effect of habit is statistically significant (*P*< 0.01; *t*= 3.472). Because of this fact, we compute the variance accounted for (VAF). The VAF is 0.38, meaning that behavioural intention is a partial mediator of habit on use behaviour (Hair et al., 2014). Another important finding from this analysis is that in future studies it may be worth including a new relationship between social influence and use behaviour, supported by a good literature background. This relationship is not foreseen in the UTAUT2 model.

Table 4.7 Mediating role of behavioural intention on independent variables

Step 1			**Step 2**			**VAF**
Paths	Beta	*t*	Paths	Beta	*t*	
			PE→BI	0.200	3.673**	
			EE→BI	0.188	2.844**	
			SI→BI	0.082	1.616	
			FC→BI	0.007	0.161	
			HM→BI	0.036	0.659	
			PV→BI	-0.007	0.131	
			HT→BI	0.392	7.313**	
			SP→BI	0.105	2.521*	
PE→UB	0.075	1.281	PE→UB	0.067	1.125	
EE→UB	-0.023	0.481	EE→UB	-0.026	0.451	
SI→UB	0.223	3.733**	SI→UB	0.228	3.389**	
FC→UB	0.124	2.609**	FC→UB	0.132	2.578*	
HM→UB	-0.107	1.617	HM→UB	-0.112	1.629	
PV→UB	0.012	0.192	PV→UB	0.019	0.312	
HT→UB	0.278	3.733**	HT→UB	0.276	3.801**	
SP→UB	0.065	1.122	SP→UB	0.050	0.869	
			BI→UB	0.271	3.746**	
			(FC→BI)×(BI→UB)	0.003	0.256	
			(SI→ BI)×(BI→UB)	0.021	1.390	
			(HT→BI)×(BI→UB)	0.106	3.472**	0.38

Notes:
1. VAF: variance accounted for;
2. PE: performance expectancy; BI: behavioural intention; EE: effort expectancy;
SI: social influence; FC: facilitating conditions; HM: hedonic motivation; PV: price value; HT: habit;
SP: self-perception; UB: use behaviour;
3. **P*<0.05; ***P*<0.01.

4.4 Discussion

4.4.1 Principal Findings

The results suggest that using our research model in a health-related area—EHR Portal acceptance by health care consumers—yields good results, explaining 49.7% of the variance on behavioural intention and 26.8% of the variance in technology use (Angst & Agarwal, 2009). The most important contributors with significant impact on behavioural intention are performance expectancy, effort expectancy, habit, and self-perception. The predictors of use behaviour are habit and behavioural intention. The inclusion of a specific construct—self-perception—related to the health care consumer area had a significant impact on understanding the adoption of EHR portals, revealing the usefulness of integrating it into our research model. Age also had a positive and significant effect on technology use. This finding suggests that older individuals use EHR portal technologies more than do younger individuals, a belief that is found in the literature. There, it is mentioned that as age increases, the need for health care services also increases, and that this is reflected in more frequent access to health care services (Alpay et al., 2010; Hunt et al., 1980). Our results were not able to support the finding that patients with chronic illness or disability are more likely to use EHR portals if they have the resources and support available. Our study had a lower proportion of people who mentioned having a chronic disability or illness compared with other studies (Fox, 2007; Millard & Fintak, 2002). This fact, together with the fact that our sample was also younger than those from other studies (Fox, 2007; Millard & Fintak, 2002) and previous findings that older people usually require more support in using technologies (Fox, 2007; Millard & Fintak, 2002; Peek et al., 2014), may explain why chronic disability did not achieve statistical significance as a moderator.

4.4.2 Theoretical Implications

Concerning our results, some of our hypotheses were supported and others not; both H1 and H2 were supported. In studies that have addressed similar problems, including those studying patient portals (Kim & Park, 2012; Or & Karsh, 2009; Wilson & Lankton, 2004), both performance and effort expectancy, originally from TAM (Davis, 1989), also had a significant positive impact. In our study, social influence did not show a significant effect on behavioural intention, thereby not supporting H3. Although the literature mentions the potential impact of social influence on the adoption of eHealth technologies (Fisher & Clayton, 2012; Thackeray et al., 2013), another recent study using UTAUT2 in health and fitness apps found no significant impact of social influence on behavioural intention (Yuan et al., 2015), which is aligned with our study results. The rejection of the facilitating conditions hypothesis, H4 (a), 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 the Internet (Rodrigues et al., 2013; Tavares & Oliveira, 2014a) and agrees with recent literature findings in eHealth (Yuan et al., 2015).

Our results were also not able to confirm that patients with chronic illness or disability are more likely to use EHR portals if they have the resources and support available, as stated in H4 (b). This stands at odds with findings reported in the literature (Fox, 2007; Millard & Fintak, 2002). Earlier studies that addressed the concept behind H4 (b) included older people and those with a higher proportion of chronic disease or disability in the sample (Fox, 2007; Millard & Fintak, 2002). This may account for the difference in the results between our study and those reported in the literature. Future studies could address the degree or type of chronic disability.

Hedonic motivation also has no significant impact on behavioural intention (H5). Hedonic motivation is defined as intrinsic motivation (e.g. enjoyment) for using EHR portals. Patients seem not to perceive the use of EHR portals as an enjoyment. This is probably because much of the use of portals is driven by the presence of a disease or a health problem, and the need for the portal is associated with that unfortunate fact—something that does not promote enjoyment (Lee et al., 2010; Osborn, Mayberry, Wallston, Johnson, & Elasy, 2013). Hedonic motivation had a positive impact on behavioural intention in an eHealth study about health and fitness apps that promote balanced lifestyles (Yuan et al., 2015). These apps potentially have a greater impact on a person's hedonic motivation than the motives leading patients to use EHR portals. H6 was not verified. In Europe, access to the majority of eHealth services is free of charge (Andreassen et al., 2007; EU Commission, 2004), so the value that is given to the patients is to enable them to perform certain tasks more effectively online. Unfortunately, that fact is not being perceived by the patients.

The impact of habit in behavioural intention and use behaviour was not moderated by age or gender; H7 (a1), H7 (a2), H7 (b1), and H7 (b2) were therefore not supported. However, the construct habit has a significant impact on both behavioural intention and use behaviour, in line with findings from literature that mention habit as a predictor of behavioural intention and use behaviour (Venkatesh et al., 2012; Yuan et al., 2015). Self-perception, a construct related to health care, has a significant impact on behavioural intention, supporting H8. People who have a greater perception that they have health problems are more likely to use EHR portals. Our study's findings are in line with other studies in this regard (Kaleta et al., 2009; Kim & Park, 2012). H9—behavioural intention will positively influence use behaviour—was also supported. Literature suggests that using specific eHealth platforms is preceded by the intention to use them (Kim & Park, 2012; Lai & Wang, 2015; Vandekar et al., 1992; Venkatesh et al., 2003; Venkatesh et al., 2012; Wilson & Lankton, 2004).

Overall, we were able to demonstrate that habit, a construct specific to consumer technology acceptance, and self-perception, which is related to the area of knowledge we are testing, are both very important in understanding the acceptance of EHR portals. Specific tailor-made models that incorporate specific changes related to the study's topic may be an effective option for studying complex areas of knowledge, such as IT health care.

4.4.3 Managerial Implications

The findings of this study have valuable managerial implications for the conceptualization, design, and implementation of an EHR portal. We found that performance expectancy and effort expectancy have a significant impact on the adoption of EHR portals. Earlier studies using TAM identified these constructs as being relevant for the adoption of patient portals (Jung & Loria, 2010; Wilson & Lankton, 2004). One of these studies adopted a qualitative TAM approach to evaluate patient portals (Jung & Loria, 2010), and the opinion of health care consumers in that study was that the design of these platforms should be simple and easy to use (Jung & Loria, 2010). 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 of the platform be tested by the potential users so that improvements can be made during the development stage to increase the platform's acceptance (Bjerkan et al., 2015; Kelders et al., 2013). Our results suggest that there is a significant impact of health care consumers' habits on EHR portal 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 (Venkatesh et al., 2012). This demands greater marketing communication effort to strengthen both the stored intention and its link to behaviour (Venkatesh et al., 2012). Promotional strategies should therefore be implemented not only on the Internet, but also in the health care institutions that the patient usually goes to (Yasnoff & Shortliffe, 2014). Because habit has been defined as the extent to which people tend to perform behaviours automatically because of learning (Venkatesh et al., 2012), it is critical that EHR portals have client support services to help users with the platform. Another important finding is that the construct that is specific to health care—self-perception—also has a significant impact on the intention to use EHR portals. Self-perception relates to the fact that the perceived, rather than the real, severity of the health complaint is the propelling force behind the action (Vandekar et al., 1992). Health care interventions that make the patient more aware of her/his health condition(s) may also promote the use of the EHR Portal. Having a population that is better educated and more aware about health status could lead to a greater adoption of eHealth services, especially EHR portals. Overall, the managerial implications mentioned here are important not only for increasing the adoption of EHR portals, but also for increasing the frequency of usage of current users, who in most cases are not frequent users (see Figure 4.4). Figure 4.6 summarizes the managerial implications.

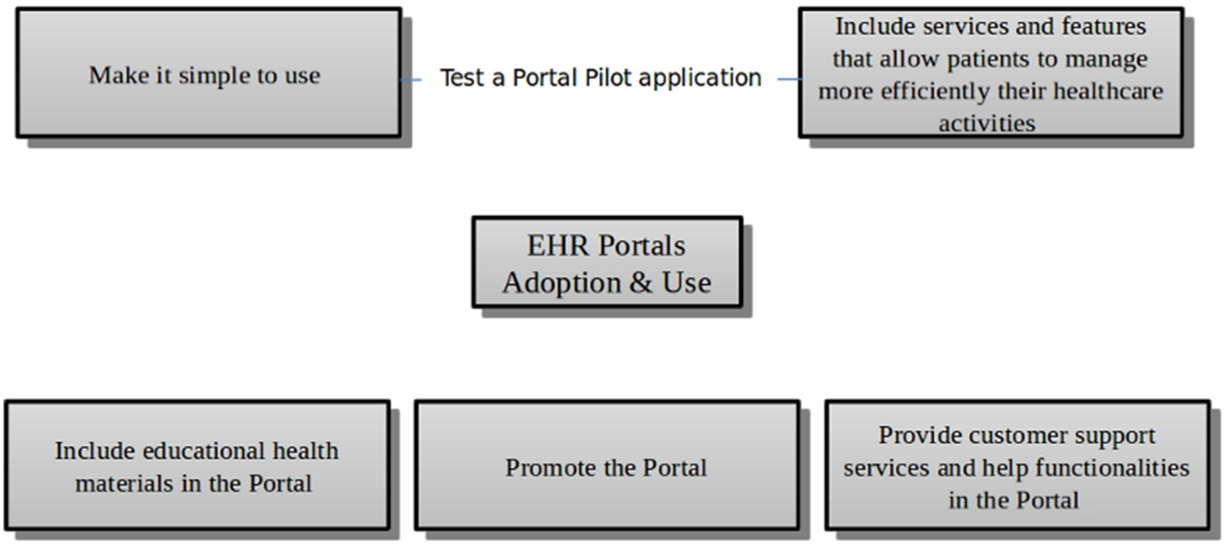


Figure 4.6 Managerial implications

4.4.4 Limitations and Future Research

We acknowledge that this research is limited by the geographic location, as it pertains to only one country and to only a sample of educational institutions. According to the literature, the technology that we are studying—EHR portals—is being used by less than 7% of the total number of health care consumers or patients (Allphin, 2012; Ancker et al., 2011; Yasnoff & Shortliffe, 2014). The literature also mentions that users and early adopters of these types of platforms are younger than the population average and have significantly higher education (Or & Karsh, 2009; Renahy et al., 2008; Roblin et al., 2009). Using a sampling strategy suitable to low-prevalence populations (Kalton & Anderson, 1986; Picot et al., 2001), we focused our sampling on educational institutions, where our target population is more concentrated (Kalton & Anderson, 1986). It is also common to find studies that evaluate eHealth portals, addressing the users of a particular portal (Lemire, Sicotte, et al., 2008; Or & Karsh, 2009; Wilson & Lankton, 2004). This is also a good strategy to target rare populations, but is also potentially biased as it reflects the opinions of only the users of a certain portal (Kalton & Anderson, 1986; Or & Karsh, 2009). Another important fact that we acknowledge as a limitation in this study is that we were not able to collect the answers at more than one point in time. As a result, we could not use experience as a moderator in this study. Difficulties targeting the user population and the sensitivity of the topic related to EHRs (Angst & Agarwal, 2009) contributed to this limitation. The impact of chronic disability/illness as a positive moderator of facilitating conditions to explain technology use—pointed out as a possibility in the literature (Fox, 2007; Millard & Fintak, 2002)—was not detected in our study. Nevertheless, only a small proportion of our sample (14.4%) mentioned having a chronic disability or illness and we did not collect information about its type or degree. Future studies might investigate this issue in greater depth.

Regarding the model tested, the inclusion of a health-related construct with significant positive impact demonstrates that it is relevant and that its inclusion is warranted. It also reveals the value of adding specific constructs related to the area in which the technology is used to existing frameworks. For future studies, it may also be advantageous to include other constructs (e.g. confidentiality) that are not specific to health care but which, according to the literature, may be influential in eHealth adoption (Angst & Agarwal, 2009; Or & Karsh, 2009), or new relationships such as the one between social influence and use behaviour. Some constructs from UTAUT2, notably hedonic motivation, do not seem to be relevant for EHR Portal adoption and, in fact, self-perception seems to be a better motivational predictor. Future studies may therefore exclude this construct in order to avoid adding redundant complexity to the model. Another interesting future contribution is to evaluate mediated moderation in the research model.

4.5 Conclusions

EHR Portal adoption is a new and growing field of study that is an important topic in government-level discussions in the European Union and the United States. In our study, we used a new model in which we identified key additional constructs and relationships based on the literature review that are specific to IT health care adoption and integrated them into UTAUT2. The research model was tested and was found to explain 49.7% of the variance in behavioural intention and 26.8% of the variance in EHR portal technology use. Of all the constructs tested, performance expectancy, effort expectancy, self-perception, and habit had the most significant effects on behavioural intention. Habit and behavioural intention had a significant effect on technology use. Two specific constructs—habit (consumer related) and self-perception (health care)—were very significant in explaining the adoption of EHR portals, showing how important it is to use specific adoption models that include constructs specific to the area. The impact of chronic disability as a moderator of facilitating conditions to explain use behaviour was not supported in our study. Not only is the adoption of EHR portals still low, but most current users of these platforms use them only infrequently. We used the results obtained in this study to provide managerial insights that may increase the adoption and usage of EHR portals.

Chapter 5- Electronic Health Record Portal Adoption: a Cross Country Analysis

5.1 Introduction

5.1.1 Overview

Our study centres on a particular type of eHealth technology, the electronic health record (EHR) portals, also called EHR patient portals (Ancker et al., 2011; Tavares & Oliveira, 2014a, 2016a, 2016b). We can define an EHR portal as a web based application that combines an EHR system and a Patient Portal (Ancker et al., 2011; Angst & Agarwal, 2009; Tavares & Oliveira, 2016b). EHR portals support patients in managing their own activities, thus making the use of the healthcare system more effective, not only from the patient care perspective, but also from the financial standpoint, due to increasing healthcare costs in several countries (Alpay et al., 2010; EU Commission, 2004; McKee et al., 2012; Metaxiotis et al., 2004). Several authors have studied the impact of cultural influences in the adoption of eHealth patient- focused technologies as well the effect of specific moderators (Hoque, 2016; Hoque & Bao, 2015; Hoque et al., 2017). Our study analyses the impact on EHR portals adoption of different healthcare systems, by using two countries that use completely different approaches (Bohm et al., 2013). The first is the national health system (NHS) model that features universal coverage, with funding from general tax revenues and public ownership of the health infrastructure, and in our study is represented by Portugal (Bohm et al., 2013). The other is the private health insurance (PHI) model coverage that is based on private insurance only, which is also the major funding source. Delivery is characterized by private ownership and in our study is represented by the United States (US) (Bohm et al., 2013).

Concerns over the confidentiality of EHR have been reported in the US, where the data in an EHR regarding a patient is currently owned by the practitioner gathering the information and/or the insurance payer covering the patient (Angst & Agarwal, 2009). Not only may the concerns about the information inside EHR be used to increase the cost of a patient health insurance in a PHI model (Angst & Agarwal, 2009; Bohm et al., 2013; Peek et al., 2014; Tavares & Oliveira, 2016b), but also the patient's perception of the price and cost of the health services is different in an NHS versus a PHI model (Angst & Agarwal, 2009; Bohm et al., 2013; Peek et al., 2014; Tavares & Oliveira, 2016b), and deserves to be evaluated if it also affects the adoption of EHR portals differently (Tavares & Oliveira, 2016b). In both the US and Europe governments seek to promote the spread and use of EHR portals (Tavares & Oliveira, 2016b).

A new guidance called “stage 2 meaningful” use was issued by the Center for Medicare & Medicaid Services (CMS) in the US (Tavares & Oliveira, 2016a, 2016b). It requires that the eligible professionals and healthcare facilities that take part in Medicare and Medicaid EHR incentive program must provide their patients secure online admission to their health information, including EHRs, and prove to the government that the patients are using them effectively (Tavares & Oliveira, 2016a, 2016b). In Europe, in addition to the usual healthcare providers (such as clinics and hospitals) that provide EHR portals, governmental institutions also make these platforms available to patients (Alpay et al., 2010; Rodrigues et al., 2013; Tavares & Oliveira, 2016b). Specifically in Portugal, the use of EHRs portals is an initiative promoted by the Portuguese government that is part of a broader e-government strategy that aims to facilitate services and communications between public services and the citizens (Tavares & Oliveira, 2016b). The most important initiative is the “SNS Portal” (NHS Portal), a national EHR Portal created by the Ministry of Health that allows all Portuguese citizens to schedule appointments with their general practitioner, obtain electronic medical prescriptions, access their medical records and exams results, and share information with healthcare providers (Tavares & Oliveira, 2016b). Recent reports point out that stage 2 meaningful use has stimulated adoption of EHRs in the US (Slight et al., 2015), but the same findings have not been confirmed in Portugal (Tavares & Oliveira, 2016b). According to the literature, adoption and continued use of a new Information Technology (IT) in general, but also in healthcare, represent different behavioural intentions (Angst & Agarwal, 2009; Karahanna, Straub, & Chervany, 1999; Zhang et al., 2015). IT adoption is the initial use of a new IT, whereas IT usage is the subsequent continued use of a new or innovative IT (Angst & Agarwal, 2009; Karahanna et al., 1999; Zhang et al., 2015). It would be interesting to verify if there are differences in the frequency of usage patterns between the two countries.

The aim of this study is to unveil a set of determinants in the adoption of EHR portals by healthcare consumers to determine if there are differences between the two countries (Portugal and the US), which we are using to represent different healthcare systems. With this purpose we suggest a new research model based on the Extended Unified Theory of Acceptance and Use of Technology (UTAUT2) in a consumer context, by integrating it with the Concern for Information Privacy (CFIP) framework.

5.1.2 Literature Review

Several models developed from theories in sociology, psychology, and consumer behaviour have been used to describe technology adoption and usage (Venkatesh et al., 2012). The aim of the current study is to focus on the EHR portals adoption from the viewpoint of the healthcare consumer. It is of the greatest importance to review the literature on this specific topic. The evaluation of the adoption of eHealth technologies by healthcare consumers still requires more attention and research due to the restricted number of studies published to date (Angst & Agarwal, 2009; Kelders et al., 2013; Or & Karsh, 2009; Tavares & Oliveira, 2016a, 2016b).

The most common adoption models used when studying eHealth and healthcare adoption by healthcare professionals are the Unified Theory of Acceptance and Use of Technology (UTAUT) (Chang et al., 2007; Tavares & Oliveira, 2016a; Vanneste et al., 2013; Yi et al., 2006) and the Technology Acceptance Model (TAM) (Dunnebeil et al., 2012; Ketikidis et al., 2012; Tavares & Oliveira, 2016a). According to the literature, EHR form the core of many eHealth applications and thus the success of these dependents greatly on the EHR adoption by the healthcare professionals (Li et al., 2013). The importance of the UTAUT model in evaluating the adoption of EHR, has been recognized in the literature by the several studies published on this specific matter (Ami-Narh & Williams, 2012; Hennington & Janz, 2007; Kim, Lee, Hwang, & Yoo, 2015; Venkatesh, Sykes, & Zhang, 2011; Wills, El-Gayar, & Bennett, 2008). Venkatesh et al. (2011) proposed a revised UTAUT for EHR system adoption and use by healthcare professionals. The revised model increased the explained variance of behavioural intention from 20% in the original model to 44% in the revised model, and is a positive indicator for the use of similar approaches with UTAUT2, with a focus on healthcare consumers (Tavares & Oliveira, 2016a; Venkatesh et al., 2012; Yuan et al., 2015). In general all four core constructs have been showed to play a role in the adoption of EHR by healthcare professionals (Ami-Narh & Williams, 2012; Hennington & Janz, 2007; Kim et al., 2015; Venkatesh et al., 2011; Wills et al., 2008), but in the latest studies, performance expectancy is demonstrating an even greater role, showing that health care professionals are now expecting that EHR systems can increase their work efficiency (Kim et al., 2015; Li et al., 2013).

When assessing the studies published in the field of consumer health information technology adoption, most studies use TAM or extensions of TAM (Ahadzadeh et al., 2015; Kim & Park, 2012; Or & Karsh, 2009; Wilson & Lankton, 2004). Neither UTAUT nor TAM were designed with the consumer in mind. Preferably, we require a model developed for the consumer use context, and UTAUT2 was developed exactly with this aim, attaining very good results (Venkatesh et al., 2012). A recent study using a UTAUT2 extension showed its usefulness in evaluating the critical determinants for the adoption of EHR portals but did not account for the confidentiality issues, nor did it compare two different countries (Tavares & Oliveira, 2016a).

Table 5.1, Sums up some of the studies done in the field of eHealth, the theory or theories supporting the studies, the dependent variable that is being explained in the study, and the most important findings. The target population in the studies was patients (Angst & Agarwal, 2009; Hoque et al., 2017; Jung & Loria, 2010; Kim & Park, 2012; Lemire, Pare, et al., 2008; Lemire, Sicotte, et al., 2008; Tavares & Oliveira, 2016a; Wilson & Lankton, 2004).

Table 5.1 eHealth adoption models

Theory	Dependent variable	Findings	Reference
TAM, integrated model (IM), motivational model (MM),	eHealth behavioural intention	▪ Users' perceived technology usefulness (PU), users' perceived ease of use (PEOU), intrinsic motivation (MT), and extrinsic motivation (EM) have significant positive influence on behavioural intention. ▪ IM does not have a better performance than TAM or than MM when predicting behavioural intention.	(Wilson & Lankton, 2004)
Elaboration likelihood model (ELM), concern for information privacy (CFIP)	EHR behavioural intention	▪ Privacy concern (CFIP) is negatively associated with likelihood of adoption. ▪ Positively framed arguments and issue involvement create more favourable attitudes toward EHR behavioural intention.	(Angst & Agarwal, 2009)
TAM (qualitative research)	eHealth services behavioural intention	▪ PU seemed to be relevant. ▪ PEOU did not seem to be an issue. ▪ Although experience is not a TAM construct, it seemed to have influenced behavioural intention.	(Jung & Loria, 2010)
TAM, plus several other constructs	Internet use behaviour as a source of information	▪ PU, concern for personal health, importance given to written media in searches for health information, importance given to the opinions of physicians and other health professionals, and the trust placed in the information available are the major predictors of use behaviour.	(Lemire, Pare, et al., 2008)
Personal empowerment	Internet use behaviour as a source of information	▪ There are three types of attitudes encouraging internet use to seek health information: consumer, professional, and community logic.	(Lemire, Sicotte, et al., 2008)
Extended TAM in health information technology (HIT)	HIT behavioural intention	▪ PEOU, PU, and perceived threat significantly influenced health consumer's behavioural intention.	(Kim & Park, 2012)
UTAUT2 extended model	Behavioural intention and use behaviour in EHR portals	▪ Effort expectancy, performance expectancy, habit, and self-perception are predictors of behavioural intention. ▪ Habit and behavioural intention are predictors of use behaviour.	(Tavares & Oliveira, 2016a)
TAM, Trust and Privacy	Intention to adopt eHealth	▪ PEOU, PU and trust are significant predictors.	(Hoque et al., 2017)

Notes: 1. EHR: Electronic health record; TAM: Technology adoption model; UTAUT2: Extended unified theory of adoption and use of technology.

Published studies point out that awareness of the lack of confidentiality and privacy concerns may reduce the adoption of eHealth tools by the patients and healthcare consumers (Angst & Agarwal, 2009; Fisher & Clayton, 2012; Fogel & Nehmad, 2009; O'Donnell et al., 2011). Studies focusing specifically on EHR show that patients are concerned about the privacy of their EHR (Angst & Agarwal, 2009). In light of these findings we decided to evaluate confidentiality in the adoption of EHR Portal via the CFIP framework (Smith et al., 1996).

5.1.3 Research Model

We can define an EHR portal as a web based application that combines an EHR system and a Patient Portal (Black et al., 2015; Tavares & Oliveira, 2016b). According to the literature most of the studies that have evaluated the adoption of patient portals, have used IT adoption models, like TAM or extended TAM; and more recently the use of UTAUT2 has also started to be implemented in patient centred eHealth tools (Ahadzadeh et al., 2015; Hoque et al., 2017; Kim & Park, 2012; Tavares & Oliveira, 2016a, 2016b). Because this model includes consumer specific constructs and EHR portals can be regarded as a healthcare consumer specific tool, the literature review suggests their use with UTAUT2 (Peek et al., 2014; Tavares & Oliveira, 2016a; Venkatesh et al., 2012; Yuan et al., 2015). In the case of UTAUT, which was originally developed to explain employee technology acceptance and use, the model itself was not developed with IT consumer adoption in mind (Venkatesh et al., 2012). UTAUT2 includes the same four core UTAUT constructs, performance expectancy, effort expectancy, social influence, and facilitating conditions plus three new constructs that are consumer specific: hedonic motivation, price value, and habit (Venkatesh et al., 2012).

In both the US and Europe governmental initiatives are underway to incorporate patient access to their EHR via EHR portals (Black et al., 2015; Kern et al., 2016; Tavares & Oliveira, 2016b), and one of the most studied topics about EHR and their acceptance by the patients is the potential confidentiality concerns, which has been addressed in the literature by using the CFIP framework (Angst & Agarwal, 2009; Ermakova et al., 2015). Since an EHR Portal incorporates all the features of a Patient Portal plus the access by the patient to EHRs (Angst & Agarwal, 2009; Black et al., 2015), it makes sense to combine both UTAUT2 and CFIP. In the US the burden of healthcare cost is much higher to the patient due to the PHI model compared to Europe, particularly to Portugal with NHS coverage (Bohm et al., 2013). The literature review also points out that the confidentiality concerns are greater in US than in Europe, including the EHR (Angst & Agarwal, 2009; Rose, 2006). Therefore we focused our multi-group analysis approach to evaluate potential adoption differences between the two countries, by using the UTAUT2, price value construct, and the CFIP framework. Figure 5.1 illustrates the new research model.

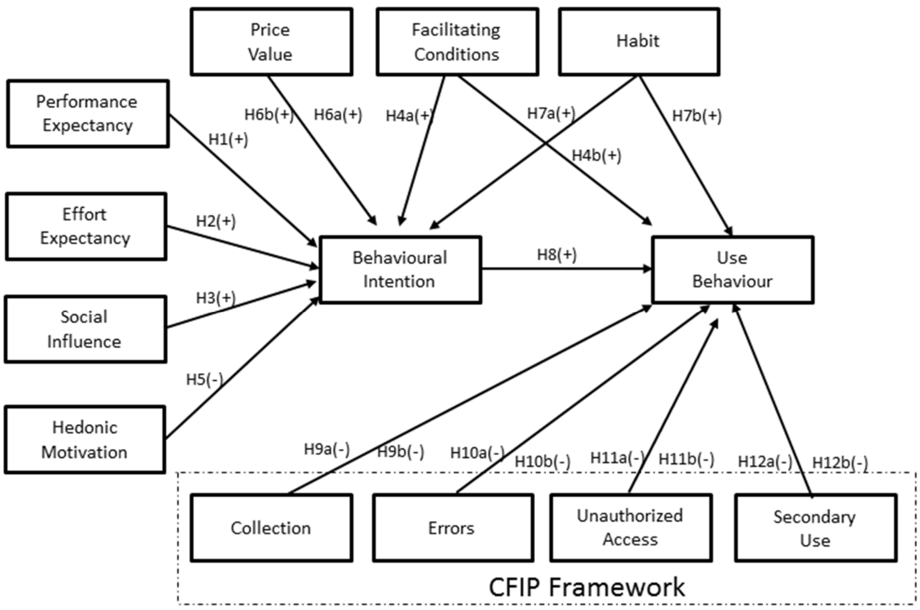


Figure 5.1 The research model

Our Hypotheses *(H)* are defined according to literature findings that may regard them as non-specific to a particular health system, or specific to a particular group analysis (US and Portugal).

UTAUT core constructs

Performance expectancy is conceptualized as the extent to which the use of a technology will provide benefits to consumers in performing specific tasks (Martins et al., 2014; Venkatesh et al., 2003). Overall healthcare consumers adopt and use more eHealth technologies that deliver benefits in performing on-line health related tasks (Alpay et al., 2010; Arsand & Demiris, 2008; Keselman et al., 2008).

H1. Performance expectancy will positively influence behavioural intention to use

Effort expectancy is the degree of ease related to consumers' usage of a specific technology (Venkatesh et al., 2003). The easier it is for patients to grasp and use an eHealth technology, the higher is the likelihood that they will use it (Alpay et al., 2010; Keselman et al., 2008).

H2. Effort expectancy will positively influence behavioural intention to use.

Social influence is the degree to which consumers recognize that others who are relevant to them believe they should use a specific technology (Venkatesh et al., 2012). Social influence may play a substantial role in eHealth adoption, since people who share the same health concerns tend to be influenced by others having the same condition (Fisher & Clayton, 2012; Thackeray et al., 2013).

H3. Social influence will positively influence behavioural intention to use

Facilitating conditions refers to consumers' perceptions of the resources and support available to perform a specific behaviour (Venkatesh et al., 2003). A potential obstacle to healthcare consumers' use of eHealth services is the absence of resources or support services that allow them to access and properly use these types of platforms (Keselman et al., 2008), suggesting that users with better conditions favour EHR portals adoption.

H4(a). Facilitating conditions will positively influence behavioural intention to use

H4(b) Facilitating conditions will positively influence use behaviour.

UTAUT2 consumer specific constructs

Hedonic motivation is linked to the motivational principle that people approach pleasure and avoid pain (Higgins, 2006; O'Brien, 2010). People use EHR portals very often when they are sick (Angst & Agarwal, 2009; Tavares & Oliveira, 2016b) and that can be regarded by many as not being a pleasant process (Lee et al., 2010). Extensive analysis has been performed in physiology and cognitive behaviour about hedonic motivation (Higgins, 2006; Venkatesh et al., 2012).

Findings from literature point out that beyond the hedonic proprieties of a value target that should contribute to the engagement strength and pleasure, there are also other factors, different from the target's hedonic proprieties, which influence engagement strength and thus contribute to the intensity of attraction or repulsion, in a manner that can be the opposite of what is expected (Higgins, 2006). Literature in healthcare care shows that people using more health services and eHealth have greater concerns about their health, more serious health problems, and have higher depression rates than the population average (Carron-Arthur, Reynolds, Bennett, Bennett, & Griffiths, 2016; Lee et al., 2010; Menec et al., 1999; Wilson & Lankton, 2004; Ybarra & Suman, 2006). Depression and poor health are also linked to less enjoyment in life (Blanco & Barnett, 2014; Pompili et al., 2016). Because most of the people that access EHR portals do it because they have a health problem (Angst & Agarwal, 2009; Tavares & Oliveira, 2016b), it would not be surprising that they do not regard the use as fun, because it is linked with a pre-existing health condition, and this is the factor different from the target's hedonic proprieties that contributes to the intensity of repulsion and the decrease of enjoyment (Higgins, 2006).

H5. Hedonic motivation will have a negative influence on behavioural intention to use.

Price Value can be defined in its essence as cognitive trade-off between the perceived benefits of the applications and the monetary cost or value benefit for using them (Dodds, Monroe, & Grewal, 1991; Venkatesh et al., 2012). In a consumer use setting, price value is an important factor since consumers must take the costs related with the acquisition of products and services (Venkatesh et al., 2012). If patients can obtain their exam results online via an EHR Portal, they can save time and transportation costs by avoiding an uncessary trip to the clinic or hospital. US citizens that need to pay out-of- pocket or via health insurances tend to give more importance to price (Angst & Agarwal, 2009; Bohm et al., 2013; Peek et al., 2014; Tavares & Oliveira, 2016b).

H6 (a). Price value will positively influence behavioural intention to use

H6 (b). Price value will positively influence behavioural intention to use in the US group and there will be a statistically significantly higher difference when compared with the Portuguese group.

Habit can be conceptualized as the degree to which people tend to perform behaviours automatically because of learning (Venkatesh et al., 2012). Habit should positively influence eHealth adoption, since in recent studies on eHealth and EHR portals habit has shown to be a positive influencer of adoption (Tavares & Oliveira, 2016a; Yuan et al., 2015).

H7(a). Habit will positively influence behavioural intention to use

H7(b). Habit will positively influence use behaviour.

The role of behavioural intention as a predictor of use behaviour has been firmly established in eHealth, with the literature suggesting that the driver of using eHealth tools and EHR portals is preceded by the behaviour intention to use them (Kim & Park, 2012; Lai & Wang, 2015; Tavares & Oliveira, 2016a; Vandekar et al., 1992; Venkatesh et al., 2003; Venkatesh et al., 2012; Wilson & Lankton, 2004).

H8. Behavioural intention will positively influence use behaviour.

CFIP framework

The CFIP framework was originally developed to measure beliefs and attitudes concerning individual information privacy related to the use of personal information in a business environment (Smith et al., 1996). It was conceptualized as being composed of four dimensions: collection, errors, unauthorized access, and secondary use (Smith et al., 1996). The CFIP framework has also been used in eHealth and in the context of EHR (Angst & Agarwal, 2009; Ermakova et al., 2015; Hwang, Han, Kuo, & Liu, 2012). Angst and Agarwal (2009) found that CFIP is negatively related to the EHR adoption and Hwang et al. (2012) confirmed the existence of substantial privacy concerns regarding secondary use and unauthorized access to EHRs. Overall the existing literature supports the elaboration of our hypothesis regarding CFIP (Angst & Agarwal, 2009; Ermakova et al., 2015; Hwang et al., 2012). Regarding the reasons to support the potential differences regarding confidentiality concerns between the two countries, previous international studies (Milberg et al., 2000; Rose, 2006) using the CFIP instrument found that consumers in countries with moderate regulatory models (e.g. the US and New Zealand) had greater privacy concerns than consumers in countries with high privacy laws regulation (e.g. the EU and more specifically Portugal) (Milberg et al., 2000; Rose, 2006; Tavares & Oliveira, 2016b). Related to healthcare and more specifically to EHR, existing literature also points out that patients, particularly in the US, seem to be more concerned about data privacy of their EHR records than their European counterparts (Angst & Agarwal, 2009; Tavares & Oliveira, 2016b)

According to the literature the mismatch between intentions and actual behaviour is likely to arise during research on sensitive topics, such as matters related with medical areas, including access to EHR, being use behaviour a more reliable measure (Angst & Agarwal, 2009; Baumgartner, 2006). Angst and Agarwal (2009) developed their very relevant study before the meaningful use implementation, when the EHR use by patients was not at a stage of diffusion (Angst & Agarwal, 2009). Due to this fact they measured the likelihood of adoption into the model as a means of estimating actual future behaviour (Angst & Agarwal, 2009). Angst and Agarwal (2009) stated in their paper that even if they were unable to collect actual use behavioural data, it should be a very important approach for future studies (Angst & Agarwal, 2009). According to the scope and characteristics of our study topic, it should be useful to use a model in which we can measure actual behaviour regarding confidentiality concerns (Angst & Agarwal, 2009; Tavares & Oliveira, 2016a) and UTAUT2 provides the possibility to have this theoretical contribution *versus* other models, like TAM, that focus on measuring behavioural intentions (Benbasat & Barki, 2007).

Collection is the concern that an extensive amount of personal information is being collected and stored in databases (Smith et al., 1996). This concern is mentioned in the literature regarding eHealth tools usage by the patients and more specifically in EHR adoption (Angst & Agarwal, 2009; Ermakova et al., 2015).

H9 (a). Collection will have a negative influence on use behaviour.

H9 (b). Collection will negatively influence use behaviour in the US group and there will be a statistically significantly higher difference when compared with the Portuguese group (Angst & Agarwal, 2009; Rose, 2006; Tavares & Oliveira, 2016b).

Errors are directly linked with the concern that protection against deliberate and accidental error in personal data is inadequate (Smith et al., 1996). This concern is mentioned in the literature regarding eHealth tools usage by the patients and more precisely in EHR adoption (Angst & Agarwal, 2009; Ermakova et al., 2015).

H10 (a). Errors will have a negative influence on use behaviour.

H10 (b). Errors will negatively influence use behaviour in the US group and there will be a statistically significantly higher difference when compared with the Portuguese group (Angst & Agarwal, 2009; Rose, 2006; Tavares & Oliveira, 2016b).

Unauthorized access is the concern that data about individuals are available to people not authorized to view or work with these data (Smith et al., 1996). This concern is stated in the literature regarding eHealth tools usage by the patients and more specifically in EHR adoption (Angst & Agarwal, 2009; Hwang et al., 2012; Smith et al., 1996)

H11 (a). Unauthorized access will have a negative influence on use behaviour.

H11 (b). Unauthorized access will negatively influence use behaviour in the US group and there will be a statistically significantly higher difference when compared with the Portuguese group (Angst & Agarwal, 2009; Rose, 2006; Tavares & Oliveira, 2016b).

Secondary use refers to the apprehension that information is collected from individuals for one purpose but is used for another secondary purpose without approval from the individuals (Smith et al., 1996). This concern is stated in the literature regarding eHealth tools usage by the patients and more precisely in EHR adoption (Angst & Agarwal, 2009; Ermakova et al., 2015; Hwang et al., 2012).

H12 (a). Secondary use will have a negative influence on use behaviour.

H12 (b). Secondary use will negatively influence use behaviour in the US group and there will be a statistically significantly higher difference when compared with the Portuguese group (Angst & Agarwal, 2009; Rose, 2006; Tavares & Oliveira, 2016b).

5.2 Methods

5.2.1 Measurement

The items were adopted from Wilson and Lankton (2004), Venkatesh et al. (2012), and Angst and Agarwal (2009) with minor modifications to adapt them to EHR portals technology. The scales' items were measured on a seven-point range scale, with a range from "strongly disagree" (1) to "strongly agree" (7). Use behaviour was measured on a different scale. The scale from UTAUT2 (from "never" (1) to "many times per day" (7)) was adjusted to "never" (1) to "every time I need" (7), since EHR portals use is not as frequent as a mobile internet use. Questions concerning, education, age and gender were also included. The questionnaire was administrated in English to the US sample and in Portuguese to the Portuguese sample, after being translated by a professional translator. Both were delivered via a web hosting. To guarantee that the content did not lose its original meaning, a back-translation was made from the Portuguese instrument to English, again done by a professional translator, and compared to the original (Brislin, 1970). The items are presented in detail in the Appendix 5.1

In advance, before the respondents could see the questionnaire, an introduction was made describing the concept of EHR portals (Appendix 5.1). The purpose of this introduction was to guarantee that respondents were conscious of this concept, and had prior contact with and knowledge of EHR portals, because the lack of this prior knowledge and contact is an exclusion criterion.

5.2.2 Data Collection

A pilot survey was executed and we obtained 30 survey questions attesting that all of the items were reliable and valid. The pilot test survey data were not included in the main survey. The literature mentions that only a very small proportion of patients, fewer than 7%, use patient portals and EHR portals (Allphin, 2012; Ancker et al., 2011; Tavares & Oliveira, 2016a, 2016b; Yasnoff & Shortliffe, 2014). Specific and suitable sampling strategies may be used to target these users, who could be regarded as a rare or low prevalence population (Kalton & Anderson, 1986; Picot et al., 2001). The literature mentions that users of these platforms have higher education than the population average (Or & Karsh, 2009; Renahy et al., 2008; Roblin et al., 2009) and as a consequence, we directed our sampling strategy to places where our target population is more concentrated (Kalton & Anderson, 1986; Picot et al., 2001), and selected education and research institutions. This approach is supported by the literature as a valid sampling strategy for low prevalence populations (Kalton & Anderson, 1986; Picot et al., 2001).

An email was sent between October of 2015 and February 2016, with the hyperlink of the survey, to a total of 2640 people at four institutions that provide education and research services, two of which were in Portugal and two in the US. The participants were informed by email about the study's goal, anonymity of the information collected, and confidentiality protection. From these we obtained 276 responses in the US (21.9% response rate) and 337 responses in Portugal (24.4% response rate). Following the removal of the invalid responses, the final sample had 597 responses, 270 from the US and 327 from Portugal. An individual questionnaire was regarded invalid if not all questions were answered. According to our statistical model we cannot use unfinished or incomplete questionnaires (Götz et al., 2010; Henseler et al., 2009).

5.2.3 Data Analysis

In order to test the research model we used the partial least squares (PLS) – structural equation modelling (SEM), which is a variance-based method having the goal of maximizing the explained variance of the endogenous latent variables (Hair et al., 2011). The main reasons to choose this method were the ability of PLS-SEM to handle complex models, a formatively measured construct is part of the structural model, and the fact that the PLS method is orientated to explain variance of the research model (Henseler et al., 2009). We used SmartPLS 2.0.M3 (Ringle et al., 2005) software to estimate the PLS-SEM. Prior to testing the structural model we examined the measurement model to evaluate construct reliability, indicator reliability, convergent validity, and discriminant validity. For complementary statistical analysis we used SPSS 21 and SAS enterprise guide 1.3.

5.3 Results

5.3.1 Sample Characteristics

The sample characteristics are shown in Table 5.2.

Table 5.2 Sample characteristics

	Average	Standard Deviation	
Age			*P <0.01*[a]
Total	33.34	10.97	
US	36.42	11.17	
Portugal	30.80	10.13	
	Frequency	**Percentage**	
Gender			*P=0.587*[b]
Male Total	257	43.05%	
Female Total	340	56.95%	
Male US	120	44.44%	
Male Portugal	137	41.90%	
Female US	150	55.56%	
Female Portugal	190	58.10%	
	Frequency	**Percentage**	
Education			*P <0.01*[b]
Undergraduate Total	192	32.16%	
Bachelor's Total	194	32.50%	
Higher than Bachelor's Total	211	35.34%	
Undergraduate US	92	34.07%	
Undergraduate Portugal	100	30.58%	
Bachelor's US	107	39.63%	
Bachelor's Portugal	87	26.61%	
Higher than Bachelor's US	71	26.30%	
Higher than Bachelor's Portugal	140	42.81%	

Notes:

1. [a] Mann–Whitney U test; [b] χ^2 test

Literature states that users of EHR portals are younger than the population average and have higher education (Or & Karsh, 2009; Renahy et al., 2008; Roblin et al., 2009), the results shown in Table 5.2 are in line with literature findings. Nevertheless, the US sample has a slightly higher age that is statistically significant when compared with the Portuguese sample. Also regarding education, there are differences between the US and Portugal. In the Portuguese sample the percentage of respondents with higher than bachelor education is 42.81%, which is greater than the US sample with 26.30%. If we make the same analysis and compare Portugal and the US, regarding people with university degree (bachelor's or more) versus undergraduate, there are no statistically significant differences between the groups (P=0.411). Gender is not statistically different between the US and Portugal. We tested normality for the variable age for each group and the Kolmogorov-Smirnov test revealed non-normal distribution in both groups. We then proceeded with a non-parametric approach to compare the two groups.

5.3.2 Usage Results

Use behaviour was measured on a scale that ranges from "never" to "every time I need" (from 1 to 7). In Table 5.3 we see that the usage differences between the US and Portugal are all statistically significant on all features of EHR Portal. These results show that the US health consumers in this sample are frequent users of EHR portals in opposition with the Portuguese sample, in which the fact that they had contact and used the technology did not make them frequent users of EHR portals (Millard & Fintak, 2002; Rodrigues et al., 2013; Weingart et al., 2006).

Table 5.3 EHR portals types of usage patterns

	Average	Median	
UB1			*P <0.01*[a]
Total	3.58	4.00	
US	4.77	5.00	
Portugal	2.60	1.00	
UB2			*P <0.01*[a]
Total	3.97	4.00	
US	4.84	5.00	
Portugal	3.25	2.00	
UB3			*P <0.01*[a]
Total	3.61	3.00	
US	5.19	6.00	
Portugal	2.31	1.00	
UB4			*P <0.01*[a]
Total	3.72	4.00	
US	5.31	6.00	
Portugal	2.41	1.00	
UB5			*P <0.01*[a]
Total	3.23	3.00	
US	4.52	5.00	
Portugal	2.17	1.00	

Notes:

1. UB1: Management of personal information and communication with health providers; UB2: Medical appointments schedule; UB3=Check their own EHR; UB4: Check your medical exam results; UB5= Request for medical prescription renewals;
2. [a] Mann–Whitney U test.

5.3.3 Measurement model

The measurement model results are shown in Tables 5.4-5.8 and Appendix 5.2. The traditional criterion used to evaluate construct reliability, is Cronbach's alpha (CA), which assumes that all the indicators are equally reliable, meaning that all of them have equal outer loadings on the construct (Hair et al., 2014). In fact, PLS-SEM prioritizes the indicators according to their individual reliability (Hair et al., 2014). For this reason the composite reliability coefficient (CR) is more appropriate for PLS-SEM, as it ranks indicators according to their individual reliability and also takes into account that indicators have different loadings, unlike CA (Hair et al., 2014).

Table 5.4 shows that all constructs in the three models have CR higher than 0.70, demonstrating evidence of internal consistency (Henseler et al., 2009; Venkatesh et al., 2012).

Table 5.4 Cronbach's alpha, composite reliability, and average variance extracted (AVE)

	AVE			Composite Reliability			Cronbach's Alpha		
Construct	Total	US	Portugal	Total	US	Portugal	Total	US	Portugal
Behavioural Intention	0.85	0.89	0.83	0.95	0.96	0.94	0.91	0.94	0.90
Collection	0.74	0.85	0.87	0.92	0.96	0.96	0.95	0.94	0.95
Effort Expectancy	0.83	0.88	0.79	0.95	0.97	0.94	0.93	0.95	0.91
Errors	0.85	0.85	0.68	0.94	0.94	0.86	0.93	0.91	0.95
Facilitating Conditions	0.65	0.69	0.62	0.88	0.90	0.86	0.81	0.85	0.79
Habit	0.62	0.70	0.67	0.83	0.87	0.86	0.74	0.82	0.75
Hedonic Motivation	0.88	0.88	0.88	0.96	0.96	0.96	0.93	0.93	0.93
Performance Expectancy	0.85	0.89	0.83	0.94	0.96	0.94	0.91	0.94	0.90
Price Value	0.90	0.90	0.89	0.96	0.97	0.96	0.94	0.95	0.94
Secondary Use	0.71	0.78	0.73	0.91	0.93	0.92	0.89	0.90	0.88
Social Influence	0.95	0.93	0.96	0.98	0.98	0.98	0.97	0.96	0.98
Unauthorized access	0.83	0.82	0.89	0.94	0.93	0.96	0.92	0.89	0.94

In order to ensure good indicator reliability, an established rule of thumb is that the latent variable should explain more than half of the indicators' variance (Hair et al., 2014). The correlation between the constructs and their indicators should be equal to or higher than 0.7 ($\sqrt{0.5} \approx 0.7$) (Henseler et al., 2009; MacKenzie et al., 2011). Still, an item is definitively recommended to be eliminated only if its outer standardized loadings are lower than 0.4 (Churchill, 1979). The measurement model (total) that includes the full sample has issues with one indicator reliability, ER1, which was removed; FC4 and HT3 are lower than 0.7, but still higher than 0.4 (Appendix 5.2). Following the removal of ER1 both the Portuguese measurement model and the US measurement model had all of their outer standardized loadings higher than 0.4 (Appendix 5.2). We decided to keep the items with loadings between 0.4 and 0.7 in all three models (total, US, and Portugal) because their deletion in any of the models did not contributed to increase the average variance extracted (AVE) or CR above the suggested threshold values (Hair et al., 2014).

The most common measure to assess convergent validity in PLS-SEM is the AVE. Using the same basis as the one used with the individual indicators an AVE value of 50% or higher means that, on average, the construct explains more than half of the variance of its own indicators

(Fornell & Larcker, 1981; Hair et al., 2014). As seen in Table 5.4, all of the indicators respect this criterion in all three models. Discriminant validity is the degree to which a construct is distinct from the other constructs in the model (Fornell & Larcker, 1981). Two measures of discriminant validity can be used (Hair et al., 2014). The first and more conservative is the Fornell- Larcker criterion (Fornell & Larcker, 1981; Henseler et al., 2009). It states that the square root of each construct's AVEs (diagonal elements) should be higher than its highest correlation with any other construct (off diagonal elements) (Fornell & Larcker, 1981; Henseler et al., 2009). As seen in Tables 5.5, 5.6, and 5.7, this criterion is achieved in all three models. In addition, another criterion can be used to assess discriminant validity which is to examine the cross loadings of the indicators, although it is regarded as a more liberal one in terms of establishing discriminant validity (Henseler et al., 2009). Precisely in this criterion, an indicator loading on the associated construct should be higher than all of its loadings in the other constructs (Chin, 1998; Götz et al., 2010). This criterion is also met, as seen in Appendix 5.2.

Table 5.5 Correlations and square roots of AVEs in the total model

	BI	CL	EE	ER	FC	HT	HM	PE	PV	SU	SI	UA	UB
BI	**0.92**												
CL	-0.06	**0.86**											
EE	0.45	-0.17	**0.91**										
ER	0.04	0.00	0.23	**0.92**									
FC	0.40	-0.11	0.68	0.26	**0.81**								
HT	0.53	0.07	0.26	-0.10	0.23	**0.79**							
HM	0.27	-0.04	0.39	0.08	0.27	0.47	**0.94**						
PE	0.57	-0.08	0.50	0.24	0.42	0.38	0.39	**0.92**					
PV	0.49	-0.03	0.39	0.09	0.35	0.44	0.33	0.41	**0.95**				
SU	0.09	-0.03	0.28	0.51	0.37	-0.12	0.03	0.22	0.11	**0.84**			
SI	0.51	0.08	0.19	-0.11	0.20	0.57	0.28	0.36	0.37	-0.10	**0.97**		
UA	0.11	0.03	0.31	0.69	0.38	-0.10	0.06	0.25	0.12	0.65	-0.14	**0.91**	
UB	0.56	0.06	0.20	-0.07	0.23	0.43	0.05	0.33	0.36	-0.03	0.49	-0.05	F

Notes:

1. BI: Behavioural intention; CL: Collection; EE: Effort expectancy; ER: Errors; FC: Facilitating conditions; HT: Habit; HM: Hedonic motivation; PE: Performance expectancy; PV: Price value; SU: Secondary use; SI: Social influence; UA: Unauthorized access; UB: Use behaviour; F: Formative
2. Diagonal elements are square roots of AVEs
3. Off-diagonal elements are correlations.

Table 5.6 Correlations and square roots of AVEs in the US model

	BI	CL	EE	ER	FC	HT	HM	PE	PV	SU	SI	UA	UB
BI	**0.94**												
CL	-0.19	**0.92**											
EE	0.61	-0.18	**0.94**										
ER	0.23	-0.07	0.23	**0.92**									
FC	0.63	-0.20	0.79	0.33	**0.83**								
HT	0.46	0.01	0.29	-0.07	0.19	**0.83**							
HM	0.29	-0.08	0.31	-0.02	0.18	0.56	**0.94**						
PE	0.68	-0.25	0.55	0.31	0.62	0.37	0.35	**0.95**					
PV	0.58	-0.16	0.48	0.27	0.48	0.41	0.34	0.50	**0.95**				
SU	0.32	-0.12	0.36	0.55	0.51	-0.15	-0.08	0.34	0.31	**0.88**			
SI	0.45	-0.04	0.24	0.04	0.24	0.55	0.48	0.43	0.30	-0.04	**0.96**		
UA	0.33	-0.04	0.37	0.64	0.51	-0.11	-0.10	0.34	0.32	0.76	-0.07	**0.91**	
UB	0.62	-0.07	0.47	0.27	0.45	0.47	0.30	0.54	0.42	0.19	0.35	0.26	F

Notes:

1. BI: Behavioural intention; CL: Collection; EE: Effort expectancy; ER: Errors; FC: Facilitating conditions; HT: Habit; HM: Hedonic motivation; PE: Performance expectancy; PV: Price value; SU: Secondary use; SI: Social influence; UA: Unauthorized access; UB: Use behaviour; F: Formative
2. Diagonal elements are square roots of AVEs
3. Off-diagonal elements are correlations

Table 5.7 Correlations and square roots of AVEs in the Portuguese model

	BI	CL	EE	ER	FC	HT	HM	PE	PV	SU	SI	UA	UB
BI	**0.91**												
CL	0.00	**0.93**											
EE	0.42	-0.17	**0.89**										
ER	0.05	-0.02	0.20	**0.82**									
FC	0.30	-0.07	0.56	0.17	**0.79**								
HT	0.63	0.14	0.29	-0.03	0.28	**0.82**							
HM	0.44	-0.02	0.45	0.07	0.34	0.50	**0.94**						
PE	0.50	0.03	0.46	0.19	0.27	0.44	0.48	**0.91**					
PV	0.36	0.00	0.35	0.05	0.27	0.47	0.44	0.33	**0.86**				
SU	-0.02	0.07	0.16	0.38	0.23	-0.09	0.08	0.12	-0.02	**0.86**			
SI	0.44	0.14	0.25	-0.07	0.25	0.57	0.32	0.32	0.34	-0.06	**0.98**		
UA	-0.11	-0.08	-0.23	-0.63	-0.25	-0.01	-0.13	-0.22	-0.08	-0.52	0.02	**0.94**	
UB	0.42	0.10	0.16	-0.06	0.22	0.41	0.16	0.22	0.21	-0.06	0.41	-0.04	F

Notes:

1. BI: Behavioural intention; CL: Collection; EE: Effort expectancy; ER: Errors; FC: Facilitating conditions; HT: Habit; HM: Hedonic motivation; PE: Performance expectancy; PV: Price value; SU: Secondary use; SI: Social influence; UA: Unauthorized access; UB: Use behaviour; F: Formative
2. Diagonal elements are square roots of AVEs
3. Off-diagonal elements are correlations

Use, which was modelled using five formative indicators, is assessed by specific quality criteria related with formative indicators. In the total model collinearity issues were detected and UB4 (check your medical exam results) with variance inflation factor (VIF) of 6.03 was eliminated from the model. With the deletion of UB4 all remaining indicators, as seen in Table 5.8, are below 5, suggesting that multi-collinearity is not an issue (Hair et al., 2014). Also the indicators' weights comply with the criteria of being statistically significant, or in case they are not significant, its outer loading must be higher than 0.5 (Hair et al., 2014).

Table 5.8 Formative indicators' quality criteria

Indicators	**VIF**	***t* value (weights)**	**Outer Loadings**
Total			
UB1	3.41	3.64**	0.94
UB2	2.10	2.70**	0.81
UB3	3.17	3.65**	0.93
UB5	2.52	0.89	0.74
US			
UB1	2.45	23.41**	0.89
UB2	2.37	14.21**	0.79
UB3	1.98	25.59**	0.91
UB5	1.85	8.43**	0.61
Portugal			
UB1	2.72	16.72**	0.95
UB2	1.70	7.86**	0.81
UB3	3.26	7.74**	0.79
UB5	2.52	5.54**	0.68

Notes:

1. VIF: Variance inflation factor;
2. ** $P < 0.01$; * $P < 0.05$;
3. UB1= Management of personal information and communication with health providers; UB2= Medical appointments schedule; UB3=Check their own EHR; UB5= Request for medical prescription renewals;

We also examined the common method variance (CMV) first using Harman's one-factor test. It revealed that the most variance explained by one factor, in this case the first factor, was 25.8%. None of the factors had variance more than the 50% threshold value (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). Thereafter the marker-variable technique (Lindell & Whitney, 2001) was used, in which we employed a theoretically unrelated construct -the marker variable (Lindell & Whitney, 2001). We found no significant correlation between the study constructs and the marker variable. We thus conclude that CMV was not a serious concern, tested by two different and known criteria (Lindell & Whitney, 2001; Malhotra, Kim, & Patil, 2006; Podsakoff et al., 2003).

Overall, all assessments are suitable. This means that the constructs may be used to test the conceptual model and its groups.

5.3.4 Structural Model

Structural model path significance levels were estimated using a bootstrap with 5000 iterations of resampling to acquire the maximum possible consistency in the results (Hair et al., 2014). The R^2 was used to assess the structural model. Overall the model explains 53% of the variance in behavioural intention and 36% of the variance in use behaviour. We used a modified version of the two-independent samples *t* test to compare path coefficients across two groups of data as described by Hair et al. (2014) to perform PLS-SEM multi-group analysis (PLS-MGA). Behavioural intention R^2 in the US group is higher than in the Portuguese group (64% versus 49%), use behaviour followed exactly the same trend (47% versus 23%). Table 5.9 presents the structural model results concerning the R^2, path coefficients significance, and identifies the statistical significance difference between groups.

Table 5.9 Structural model results

Dependent variables	Independent variables	$\hat{\beta}_{total}$	$\hat{\beta}_{PT}{}^{a}$	$\hat{\beta}_{US}$	$t_{total}{}^{b}$	$t_{PT}{}^{b}$	$t_{US}{}^{b}$	$\hat{\beta}_{(US-PT)}$	$t_{(US-PT)}{}^{b}$	R^2 Total	R^2 PT	R^2 US
BI										0.53	0.49	0.64
	PE	0.285	0.190	0.292	6.61**	3.29**	3.86**	0.102	1.07			
	EE	0.160	0.177	0.163	3.17**	2.61**	1.99*	-0.014	0.13			
	SI	0.198	0.083	0.149	5.42**	1.57	2.91**	0.066	0.89			
	FC	0.062	0.001	0.181	1.51	0.02	2.15*	0.180	1.87			
	HM	-0.141	0.026	-0.138	3.63**	0.44	2.66**	-0.164	2.10*			
	PV	0.152	-0.004	0.196	3.62**	0.08	3.24**	0.200	2.46*			
	HT	0.255	0.436	0.188	6.74**	7.57**	3.60**	-0.248	3.20**			
UB										0.36	0.23	0.47
	FC	0.052	0.103	0.106	1.19	2.09*	1.26	0.003	0.04			
	HT	0.145	0.209	0.276	2.96**	2.59**	4.55**	0.067	0.67			
	CL	0.088	0.073	0.027	1.49	1.26	0.45	-0.046	0.56			
	ER	-0.018	-0.115	0.174	0.36	1.21	2.63**	0.289	2.50*			
	SU	0.000	-0.066	-0.091	0.00	0.76	1.16	-0.025	0.22			
	UA	-0.098	-0.085	0.064	1.47	0.76	0.70	0.149	1.03			
	BI	0.480	0.249	0.395	10.57**	3.30**	4.36**	0.146	1.26			

Notes:

1. [a] PT: Portugal; [b] ** $P < 0.01$; * $P < 0.05$.
2. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; FC: Facilitating conditions; HM: Hedonic motivation; PV: Price value; HT: Habit; BI: Behavioural intention; CL: Collection; ER: Errors; UA: Unauthorized access; SU: Secondary use; UB: Use behaviour.

5.4 Discussion

5.4.1 Principal Findings

Our results seem to point out that in fact US and Portugal are in different stages, and that Portugal is still in the initial stage of adoption. Consequently, the factors determining user acceptance should differ in these two different stages (Angst & Agarwal, 2009; Karahanna et al., 1999; Zhang et al., 2015). The results reported in Table 5.3 seem to support these theoretical findings, suggesting that the Portuguese group is still in its initial stage of adoption with a low frequency of usage, whereas the US group seems to be already in the continued usage of EHR portals. Also, the factors that determine user acceptance are not exactly the same between the two groups. The more consistent and established use of EHR portals by the US group also seems to contribute to higher explanatory power of the model with the US sample *versus* the Portuguese sample (Götz et al., 2010; Hair et al., 2014; Hair et al., 2011). The implementation of stage 2 meaningful use in the US leads to incentive payments to clinicians and hospitals (Slight et al., 2015), that according to recent reports have stimulated the adoption of EHR. These mandatory polices in the US, something that did not happen in Portugal to implement EHR portals (Tavares & Oliveira, 2016b), may have resulted in a greater effort to encourage the continuous usage of EHR portals by the patients when compared with Portugal.

5.4.2 Theoretical Implications

Performance expectancy ($\hat{\beta}_{\text{total}}$=0.285; P<0.01) and effort expectancy ($\hat{\beta}_{\text{total}}$=0.160; P<0.01) obtained statistically positive impacts on behavioural intention in the total model and in both groups, as reported in Table 5.9. Concerning the results obtained in studies that addressed similar issues, both performance and effort expectancy, originally from TAM (Davis, 1989), also had significant positive impacts, as reported in eHealth adoption studies including patient portals (Or & Karsh, 2009; Wilson & Lankton, 2004). These findings support both hypotheses H1 and H2, as reported in Table 5.10. Social influence ($\hat{\beta}_{\text{total}}$=0.198; P<0.01) had a positive and significant impact on behavioural intention in the total model, supporting hypothesis H3, and also a statistically significant impact in the US group ($\hat{\beta}_{\text{US}}$=0.149; P<0.01). Literature also supports that social influence could play a role in the adoption of eHealth platforms and that this influence may come from support groups and social media (Fisher & Clayton, 2012; Thackeray et al., 2013). Facilitating conditions did not show a significant impact in predicting behavioural intention and use behaviour in the total model. Although H4(a) and H4(b) are not supported in the total model, in the group analysis facilitating conditions ($\hat{\beta}_{\text{US}}$=0.181; P<0.05) had a positive impact on behavioural intention in the US and a positive impact ($\hat{\beta}_{\text{PT}}$=0.103; P<0.05) on use behaviour in Portugal. According to the literature, adoption and continued use of new IT technologies in general, but also in healthcare, represent different behavioural intention (Angst & Agarwal, 2009; Karahanna et al., 1999; Zhang et al., 2015). What the results seem to point out is that in a country like Portugal, in the initial stage of adoption, the availability of resources and support may directly increase use. Concerning the US, with an already higher frequency of usage, the availability of resources has a positive impact on behavioural intention, which promotes the continuous use of EHR portals. Although there is some evidence in the literature to support these findings (Karahanna et al., 1999; Zhang et al., 2015), we believe that this topic should be further investigated in future studies, because when these results are analysed together the contributions of the non-significant paths of each country on the total model, result that their influence is to make H4 not significant (different facilitating conditions behaviours between the countries).

Table 5.10 Summary of findings regarding Hypotheses

Path	Beta	t-value	Hypothesis	Result
PE → BI	0.285	6.61**	H1	Supported
EE → BI	0.160	3.17**	H2	Supported
SI → BI	0.198	5.42**	H3	Supported
FC → BI	0.062	1.51	H4(a)	Not supported
FC → UB	0.052	1.19	H4(b)	Not supported
HM → BI	-0.141	3.63**	H5	Supported
PV → BI	0.152	3.62**	H6(a)	Supported
(PV_{US} → BI_{US}) - (PV_{PT} → BI_{PT})	0.200	2.46*	H6(b)	Supported
HT → BI	0.255	6.74**	H7(a)	Supported
HT → UB	0.145	2.96**	H7(b)	Supported
BI→ UB	0.480	10.57**	H8	Supported
CL→ UB	0.088	1.49	H9(a)	Not supported
(CL_{US} → UB_{US}) - (CL_{PT} → UB_{PT})	-0.046	0.56	H9(b)	Not supported
ER→ UB	-0.018	0.36	H10(a)	Not supported
(ER_{US} → UB_{US}) - (ER_{PT} → UB_{PT})	0.289	2.50*	H10(b)	Not supported
UA→ UB	-0.098	1.47	H11(a)	Not supported
(UA_{US} → UB_{US}) - (UA_{PT} → UB_{PT})	0.149	1.03	H11(b)	Not supported
SU→ UB	0.000	0.00	H12(a)	Not supported
(SU_{US} → UB_{US}) - (SU_{PT} → UB_{PT})	-0.025	0.22	H12(b)	Not supported

Notes:

1. PE: Performance expectancy; EE: Effort expectancy; SI: Social influence; FC: Facilitating conditions; HM: Hedonic motivation; PV: Price value; HT: Habit; BI: Behavioural intention; CL: Collection; ER: Errors; UA: Unauthorized access; SU: Secondary use; UB: Use behaviour
2. ** $P < 0.01$; * $P < 0.05$;

We confirmed that hedonic motivation (H5) does have a significant negative effect ($\hat{\beta}_{total}$=-0.141; P<0.01) on behavioural intention. Another important finding is that the US group has a statistically significant difference *versus* the Portuguese group. In fact, this is the group that uses the EHR portals more frequently, and during its continuous usage does not perceive it as an enjoyment, but probably more as a need (Tavares & Oliveira, 2016a; Thackeray et al., 2013). Literature in healthcare shows that people using more health services and eHealth have greater concerns about their health, more serious health problems, and have higher depression rates than the population average (Lee et al., 2010; Menec et al., 1999; Wilson & Lankton, 2004; Ybarra & Suman, 2006). Depression and poor health are also linked with less enjoyment in life (Blanco & Barnett, 2014; Ybarra & Suman, 2006). Literature points out that there are also other factors, different from the target's hedonic proprieties, that influence engagement and can thus contribute to repulsion (Higgins, 2006). Therefore it is not surprising that patients do not regard the EHR Portal use as fun, because it is linked with a pre-existing health condition, and this is the factor different from the target's hedonic proprieties, which contributes to the intensity of repulsion and the decrease of enjoyment (Higgins, 2006). This shows that findings from other consumer related areas that point out hedonic motivation as having a positive influence over adoption (Venkatesh et al., 2012) do not necessarily apply in the case of EHR portals. Because in EHR portals there is an external factor, different from the hedonic proprieties influencing the results, future research may use constructs related with the health belief model (HBM), such as perceived threat (Ahadzadeh et al., 2015; Kim & Park, 2012), which links the perceived health concerns with the adoption of EHR portals, which could be a more straightforward way to measure the same effect (Ahadzadeh et al., 2015; Kim & Park, 2012).

Hypothesis H6(a), that price value ($\hat{\beta}_{total}$=0.152; P<0.01) would have a positive impact on behavioural intention, was verified. There are also statistically significant differences between the US group and the Portuguese group, pointing out that in a healthcare context like the US', where patients pay directly out of their pocket or via an expensive health insurance (Angst & Agarwal, 2009; Zhang et al., 2015), more value is attributed to the EHR portals' added value of performing these activities in a more cost-effective manner, compared to the Portuguese patients, who are covered by an NHS that features universal coverage (Bohm et al., 2013). Our results, together with what is stated in the literature, support hypothesis H6(b), that patients with a PHI model coverage perceive greater price value advantages of an EHR portal than do patients with an NHS model (Angst & Agarwal, 2009; Bohm et al., 2013). The construct habit has a statistically significant impact on both behavioural intention ($\hat{\beta}_{total}$=0.255; P<0.01) and use behaviour ($\hat{\beta}_{total}$=0.145; P<0.01), in line with findings from literature that refer habit as a predictor of behavioural intention and use behaviour in eHealth tools and EHR portals (Tavares & Oliveira, 2016a; Yuan et al., 2015), supporting both hypotheses H7(a) and H7(b). Our study's findings are also in line with those of other studies, that using specific eHealth and EHR portals is preceded by the intention to use ($\hat{\beta}_{total}$=0.480; P<0.01) them (Kim & Park, 2012; Tavares & Oliveira, 2016a), supporting hypothesis H8.

The hypotheses related with CFIP constructs (H9-H12) were not supported. We tested people who know about the technology, adopt, and use it. People who already use EHR portals may have a different behaviour as compared with never users regarding confidentiality issues, and this may explain the unexpected behaviour toward confidentiality in our study (Angst & Agarwal, 2009). One of the CFIP dimensions, error ($\hat{\boldsymbol{\beta}}_{US}$=0.174; P<0.01), is linked in our study with a higher use of EHR portals in the US. This result may look surprising, but Angst and Agarwal (2009) tested with success that individuals with a stronger Concern for Information Privacy should have a more favourable attitude toward EHR use under conditions of positive argumentation and communication in favour of EHR use. One possible explanation for this specific dimension from CFIP, and not the others, to be statistically significant is probably because the US patients perceive the reduction of medical errors as the biggest advantage of EHR (Angst & Agarwal, 2009), and they want to be reassured that the health entities comply with this objective. There is also a statistically significant difference between US and Portugal in the error dimension. Again, this is in line with the stage 2 meaningful use objective to promote the national use of EHR by the US patients versus Portugal, where this kind of national initiative was not implemented in a structured manner (Slight et al., 2015; Tavares & Oliveira, 2016b). This is a complex topic and its justification is far from being definitive. It only reinforces the literature findings that confidentiality issues in healthcare are a very complex topic (Angst & Agarwal, 2009; Tavares & Oliveira, 2014a). According to the literature, patient acceptance in consumer health technology is related to more educated and younger patients (Or & Karsh, 2009; Zhang et al., 2015). The Portuguese sample is younger and more educated, but with less acceptance and usage. Nevertheless, both groups may be regarded as young, the US with an average of 36.42 years versus 30.80 of the Portuguese. Also regarding education, the Portuguese group has a greater proportion of people with more than a Bachelor's degree. But in a more pragmatic approach, if we compare both groups with having or not a university degree, there are no statistically significant differences between the two groups. Overall the socio- demographics in our study do not seem to be relevant in the difference between the group's results. Figure 5.2 and Figure 5.3 show the structural model results for each country.

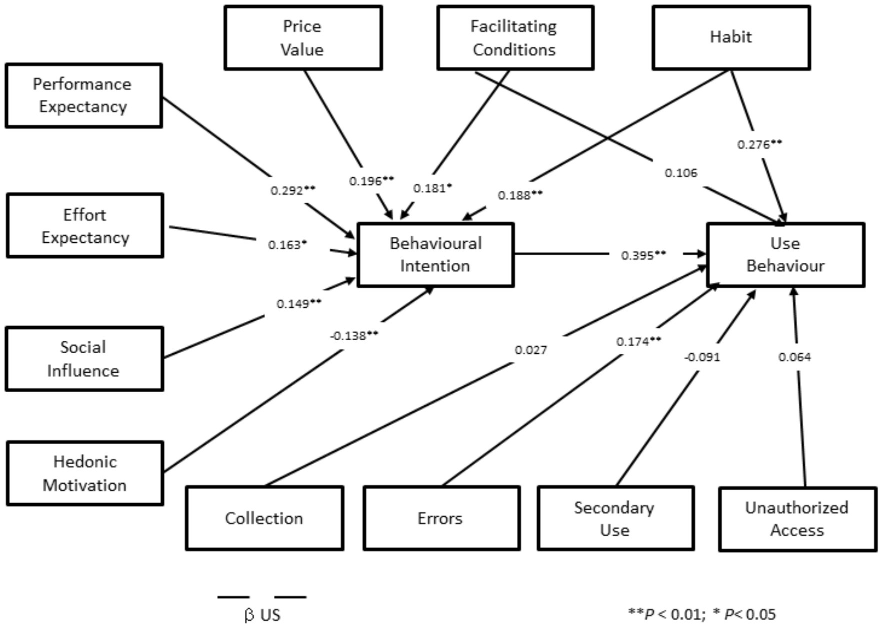


Figure 5.2 Structural model results for US

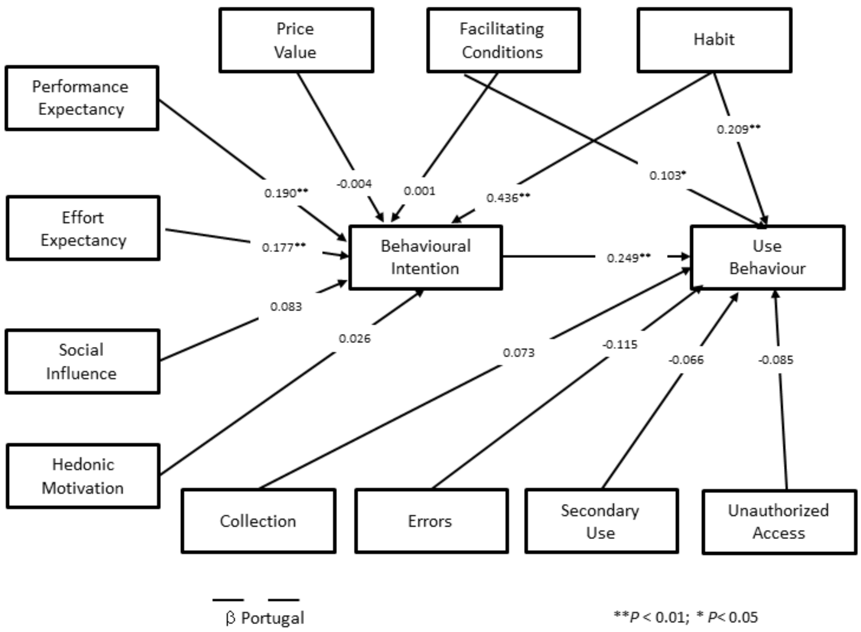


Figure 5.3 Structural model results for Portugal

5.4.3 Managerial Implications

A study that evaluates an important topic like EHR portals should provide managerial insights that can be helpful in the design and implementation of this specific technology. That is exactly what we address in this section. Our study results point out that there is a significant impact of patients' habit on EHR portals usage. Habit has been defined as the degree to which people tend to perform behaviours repeatedly because of learning (Venkatesh et al., 2012). So it is important that EHR portals have customer support services to help users with the platform. Also, the fact that facilitating conditions seem to play a significant role (see Table 5.9) on use behaviour in the Portuguese group and behavioural intention in the US group is additional evidence in favour of customer service support, since the definition of facilitating conditions is related to perceptions of the resources and support available for a particular IT platform (Venkatesh et al., 2003; Venkatesh et al., 2012).The study also identified that both performance expectancy and effort expectancy have important influences on the adoption of EHR portals. Previous studies using TAM identified both constructs as being significant for the adoption of eHealth technologies and EHR portals, and suggest that these technologies should be simple and easy to use (Jung & Loria, 2010; Tavares & Oliveira, 2016a; Wilson & Lankton, 2004). When redeploying or designing an EHR portal, we should thus strive to make it easy and simple for the healthcare consumers to use (Bjerkan et al., 2015; Kelders et al., 2013; Trevena et al., 2013). 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 (Lemire, Pare, et al., 2008; Thackeray et al., 2013), digital strategies to promote eHealth tools by using social networks (e.g. Facebook) should be useful in promoting the adoption and use of EHR portals. Because price value is also a significant construct in our study, the value of the EHR portals and the way they may help patients to manage their health in a more cost-effective manner should be actively promoted to them. According to the literature, to avoid confidentiality concerns from reducing the acceptance of EHR portals, positive argumentation and communication in favour of their use should be actively promoted to patients (Angst & Agarwal, 2009). There is evidence that a subset of patients during meaningful use, exposed to EHRs via their physicians, who explained the advantages of EHR, have more positive attitudes toward EHRs than those without that exposure (Ancker, Brenner, et al., 2015).

5.4.4 Limitations and Future Research

Only a small proportion of the population, less than 7%, uses EHR portals (Allphin, 2012; Ancker et al., 2011; Tavares & Oliveira, 2016a, 2016b; Yasnoff & Shortliffe, 2014), and according to the literature these individuals are younger and more educated than the population average (Or & Karsh, 2009; Renahy et al., 2008; Roblin et al., 2009). This population profile is more concentrated in research and education institutions, making such places a good target for sampling, since this a suitable strategy to investigate low prevalence populations (Kalton & Anderson, 1986; Picot et al., 2001). Although the fact that our sampling is restricted to education and research institutions, and this can be regarded as a limitation of our study, it can be justified by the type of population we are targeting (Kalton & Anderson, 1986). According to Karahanna et al. (1999), adoption and continued use of an IT innovation represent different behavioural intentions. In our study, the US group is in a stage of continuous use of EHR portals, unlike the situation in the Portuguese group. Taking these facts into account, Rogers' innovation diffusion theory could be included in future models to study EHR portals acceptance, as it was with other eHealth technologies (Zhang et al., 2015). Comparing people who already use EHR portals, as in our study, with those who never have in future studies (regarding confidentiality issues) may also explain different behaviour toward confidentiality (Angst & Agarwal, 2009). Our study did not probed the EHR Portal users about the potential effect of positive message framing to which they may have been exposed, that could explain the non-impact of CFIP on adoption (Ancker, Brenner, et al., 2015; Angst & Agarwal, 2009), and future studies may address this topic. Constructs related with the HBM such as perceived threat may replace hedonic motivation in future studies, since they provide a more direct measure of the intrinsic motivation of the patients toward EHR portals (Ahadzadeh et al., 2015; Kim & Park, 2012). The CFIP framework did not reveal a statistically significant role in our study, but provided theoretical and managerial insights that invite further analysis in future studies. PLS path modelling is primarily used to develop theories in exploratory research (Hair et al., 2014). It does this by focusing on explaining the variance in the dependent variables when examining the model and is particularly suitable for multi-group analysis (Götz et al., 2010; Hair et al., 2014; Hair, Sarstedt, Ringle, & Mena, 2012) aligned with our study goals. PLS-SEM does not have an adequate global goodness-of-model fit measure, and its use for confirmatory theory testing is limited, and in this case covariance based (CB)-SEM is a more appropriate option (Hair et al., 2014; Hair et al., 2012), and should be used in future studies when more information about the study context is gathered, and other constructs, moderators, or theories beyond CFIP could play a more significant role.

5.5 Conclusions

EHR portals adoption is a recent and emergent field of study that is an important topic in both the EU and the US (Slight et al., 2015; Tavares & Oliveira, 2016b). Among the constructs tested, performance expectancy, effort expectancy, social influence, hedonic motivation (negative influence), price value, and habit had the most significant effects over behavioural intention. Habit and behavioural intention had a significant effect over use behaviour. Price value had a statistically significant impact on behavioural intention in the US group in opposition to the non-significant impact of the Portuguese group. Also regarding price value, the differences between groups are significant, demonstrating that in a country like the US, where the healthcare cost is very expensive to the patient, the value of EHR portals is better perceived by the patients (Angst & Agarwal, 2009; Bohm et al., 2013; Tavares & Oliveira, 2016b). Our study focused on healthcare consumers who are already users of EHR portals, and found that confidentiality concerns do not decrease the current usage of EHR portals by the patients or healthcare consumers. Other studies that focused on the intention to use (Ermakova et al., 2015), report that confidentiality concerns could be a barrier for future use. It seems that when someone starts using an EHR Portal, the impact of confidentiality concerns on effective use is not significant. It seems that when a patient overcomes the barrier of potential intention to use, to effective opt-in use of an EHR Portal, confidentiality concerns, measured via CFIP in our study are no longer a significant obstacle. There is evidence in the literature that with positive argumentation about EHR portals, confidentiality concerns will no longer significantly impact adoption (Angst & Agarwal, 2009). There is recent literature about the on-going implementation of meaningful use that seems to support this evidence (Ancker, Brenner, et al., 2015). In any event our study is exploring a very recent topic, studying effective users of EHR portals and future studies are required to evaluate our study findings even deeper. Overall, the model explains 53% and 36% of the variance in behavioural intention and use behaviour, with these values being higher in the US group, 64% on behavioural intention and 47% on use behaviour. The US group also reveals much higher and significant usage patterns compared with the Portuguese group. We applied the results obtained in this research to deliver managerial insights that may increase the usage and adoption of EHR portals.

Chapter 6- Electronic Health Record Portal Adoption- A New Integrated Model Approach

6.1 Introduction

6.1.1 Overview

The Electronic Health Record (EHR) Portal or an EHR Patient Portal it is a technology that combines an EHR system and a Patient Portal where patients can communicate with their health care providers (e.g., send messages, schedule medical appointments, request prescription refills online), and access their EHR and medical exams results (Ancker et al., 2011; Tavares & Oliveira, 2016a, 2016b). EHR portals have received great attention at the governmental level worldwide (Kern et al., 2015; Tavares & Oliveira, 2016a, 2016b). In the US, the support given to EHRs, via meaningful use program, led the federal government to commit unparalleled resources to support adoption of EHRs, through incentive payments that can reach up to $27 billion over 10 years (Blumenthal & Tavenner, 2010; Kern et al., 2015). EHR portals are a relevant topic not only in the US, but also in Europe, through several projects, such as the European Patients Smart Open Services (epSOS) initiative, promoted by the EU Commission (Tavares & Oliveira, 2016b). EpSOS focuses on developing a practical Information and Communication Technology (ICT) infrastructure that will enable secure access to patient information, including EHR amongst different European countries (Tavares & Oliveira, 2016b).

Most of the EHR portals usage in the developing countries ranges between 5-10% of the total annual target population that they aim to reach (Gheorghiu & Hagens, 2017; Tavares & Oliveira, 2016b). Most of the EHR portals are implemented at organizational or healthcare unit level, but there are some examples of National coverage EHR portals (Gheorghiu & Hagens, 2017; Tavares & Oliveira, 2016b). Probably the most successful nationwide implementation of an EHR Portal is the Sundhed.dk in Denmark with 1.1 million unique registered users, approximately 20% coverage of the Danish population (Gheorghiu & Hagens, 2017). In Portugal a National Health Service (NHS) Portal was implemented, but its success was more limited, with only approximately 7% of registered users versus the population coverage and a low level of overall use (Tavares & Oliveira, 2016b). The number of registered users does not provide information about their usage pattern. Taking this into account, a nationwide survey using a sample of randomly generated mobile numbers was applied in our study.

The goals of this study are to estimate the percentage of EHR Portal users among the Portuguese population and understand the factors that drive health care consumers to adopt and use EHR portals. We apply three different theories to build our research model. The Extended Unified Theory of Acceptance and Use of Technology (UTAUT2), the Health Belief Model (HBM) theory, and the Diffusion of Innovation (DOI) theory. In the research model section a more detailed rationale explaining why we combined these three theories is provided.

6.1.2 Theoretical Background

Our study goal is to focus on the EHR portals adoption from the standpoint of the health care consumer. According to the literature, assessing the adoption of eHealth tools by health care consumers still demands more effort due to the still low number of studies published to date, and in view of the importance of the topic (Angst & Agarwal, 2009; Tavares & Oliveira, 2016b). The most frequently used adoption models when studying eHealth adoption by health care professionals are the Unified Theory of Acceptance and Use of Technology (UTAUT) (Chang et al., 2007; Tavares & Oliveira, 2016a; Vanneste et al., 2013) and the Technology Acceptance Model (TAM) (Dunnebeil et al., 2012; Ketikidis et al., 2012; Tavares & Oliveira, 2016b). When evaluating the studies published in the field of consumer health information technology adoption, most of the research use TAM or extensions of TAM (Hoque et al., 2017; Kim & Park, 2012; Lemire, Pare, et al., 2008; Wilson & Lankton, 2004). Although the studies that used extended TAM, used other models and theories with TAM to adapt it to the consumer health technology context (see Table 6.1), TAM was not envisaged with the consumer focus in mind. Rather, we need a model developed for the consumer use setting, and UTAUT2 was developed precisely with this purpose, achieving good results (Venkatesh et al., 2012). A recent study using an UTAUT2 extension demonstrated its usefulness in assessing the critical determinants for the adoption of EHR portals, in which the construct habit, which is a consumer specific construct, was the one with greatest impact on the adoption of EHR portals (Tavares & Oliveira, 2016a). This fact shows the importance of using research models that are consumer specific.

Table 6.1 eHealth patient focused adoption models

Theory	Dependent variable	Findings	Reference
TAM, integrated model (IM), motivational model (MM),	eHealth BI	▪ Users' perceived technology usefulness (PU), users' perceived ease of use (PEOU), intrinsic motivation (MT), and extrinsic motivation (EM) have significant positive impact on behavioural intention (BI). ▪ IM does not have better results than TAM or MM when predicting BI.	(Wilson & Lankton, 2004)
UTAUT2 plus CFIP (cross – country analysis: US vs Portugal)	BI and UB in EHR portals	▪ BI drivers are performance expectancy (PE), effort expectancy (EE), social influence (SI), hedonic motivation (HM), price value (PV), and habit (HT). The predictors of use behaviour (UB) are HT and BI. ▪ SI, HM, and PV are only predictors in the US group. ▪ Confidentiality issues do not seem to influence acceptance.	(Tavares & Oliveira, 2017)
TAM, Trust and Privacy	Intention to adopt eHealth	▪ PEOU, PU, and trust are significant predictors.	(Hoque et al., 2017)
UTAUT2	BI and UB in EHR portals	▪ The BI drivers are PE, EE, SI, and HT. ▪ HT and BI are drivers of UB	(Tavares, Goulao, & Oliveira, in press)
DOI (mix of qualitative/ quantitative study)	Adoption rate of an e-appointment scheduling service (EAS)	▪ The influence of the perceived attributes of the EAS according to the DOI theory helps explaining the low adoption and use. ▪ Low socio-economic status and lower educational level influence negatively the EAS adoption rate.	(Zhang et al., 2015)
Extended TAM in health information technology (HIT)	HIT BI	▪ PEOU, PU, and perceived threat significantly influenced health consumer BI.	(Kim & Park, 2012)
UTAUT2 extended model	BI and UB in EHR portals	▪ EE, PE, HT, and SP are predictors of BI. ▪ HT and BI are predictors of UB.	(Tavares & Oliveira, 2016a)
Institutional theory and UTAUT	Patient Portal UB	▪ Coercive and mimetic pressures significantly influence patient portal UB. ▪ Normative pressure was found to be not relevant	(Bozan et al., 2015)

Notes: 1. CFIP: Concern for information privacy; DOI: Diffusion of innovation; EHR: Electronic health record; TAM: Technology adoption model; UTAUT: Unified theory of adoption and use of technology; UTAUT2: Extended unified theory of adoption and use of technology;

Although EHR portals are consumer oriented technologies, since a patient can be viewed as a health care consumer, the use of a model like UTAUT2 should not be regarded as enough to explain the complexity of EHR Portal adoption (Kim & Park, 2012; Tavares & Oliveira, 2016a; Venkatesh et al., 2012). Several studies that used constructs or frameworks related with the HBM, demonstrated their usefulness and statistical significance in explaining health information consumer adoption (Ahadzadeh et al., 2015; Kim & Park, 2012; Tavares & Oliveira, 2016a). The HBM advocates that belief in health risk predicts the likelihood of engaging in health behaviour, or an alternative way to look into it, considers that the perceived, instead of the real severity of the health complaint could be the driving force behind the action (Kim & Park, 2012; Vandekar et al., 1992). Evidence in the literature shows that the global usage of EHR portals is still limited (Gheorghiu & Hagens, 2017; Kern et al., 2015; Nøhr et al., 2017; Tavares & Oliveira, 2016b). Since the rate of adoption is still low in the use of EHR portals, literature that has addressed the eHealth patient technologies under the scope of DOI also mentioned low level of global use and identified the users as early adopters (Yi et al., 2006; Zhang et al., 2015). Earlier studies that focused on understanding eHealth patient centred technologies and EHR portals identified both performance expectancy and effort expectancy as important predictors of behavioural intention to use (Kim & Park, 2012; Tavares et al., in press; Tavares & Oliveira, 2016a, 2017; Wilson & Lankton, 2004). Both performance expectancy and effort expectancy have their equivalents within DOI theory as relative advantage and complexity (Oliveira, Thomas, Baptista, & Campos, 2016; Yi et al., 2006), providing another strong argument to use DOI theory when studying EHR portals (Tavares & Oliveira, 2017; Zhang et al., 2015). This study included intention to recommend as a dependent variable. According to our knowledge, this is the first time that intention to recommend is studied in the field of EHR portals adoption (Hoque et al., 2017; Kim & Park, 2012; Oliveira et al., 2016; Tavares & Oliveira, 2016a, 2017). Understanding if current users of new technologies that have a low level of adoption can be used to promote them is a valuable asset that should be evaluated (Oliveira et al., 2016).

6.1.3 Research Model

Since EHR portals are a new health consumer focused technology (Tavares & Oliveira, 2016a, 2016b) our research model is a combination of UTAUT2, which was developed as an adoption model adapted to the IT consumer environment (Venkatesh et al., 2012), self-perception, a construct from the HBM (Chan et al., 1998; Kaleta et al., 2009; Kim & Park, 2012; Tavares & Oliveira, 2016a; Vandekar et al., 1992), and a framework based on the DOI (Moore & Benbasat, 1991; Oliveira et al., 2016; Yi et al., 2006) that address the underlying reasons of adopting new and innovative technologies. We believe that the combination of these three theories will cope with the complexity of studying the underlying factors of EHR portals adoption. We also made some improvements in our research model concerning the theories we used. In the UTAUT2 framework we did not use the construct hedonic motivation. Hedonic motivation is conceptualized as intrinsic motivation (e.g. pleasure or enjoyment) (Venkatesh et al., 2012). People use EHR portals frequently when they are ill (Ancker et al., 2011) and that can be viewed by many as not being an enjoyable activity (Lee et al., 2010). Recent literature confirms no consistent and relevant results in predicting the adoption of EHR portals with hedonic motivation (Tavares et al., in press; Tavares & Oliveira, 2016a, 2017). What literature evidence shows is that constructs related with the HBM, such as perceived health risk or self -perception, are much better motivation predictors of adoption of EHR portals than hedonic motivation (Kim & Park, 2012; Tavares & Oliveira, 2016a). We also used intention to recommend as a dependent variable. This is as a variable that has not been used in the literature to explain adoption of EHR portals (Or & Karsh, 2009; Tavares & Oliveira, 2016b, 2017). Instead, it has been used in other technologies to explain adoption, such as mobile payment (Oliveira et al., 2016), that were also regarded as relatively new and with low usage level (Oliveira et al., 2016), like EHR portals (Tavares & Oliveira, 2016a). In these kinds of technologies, providers now start to rely on current or potential users to recommend them to others (Oliveira et al., 2016). That is why we included intention to recommend in our research model. Figure 6.1 illustrates the new research model.

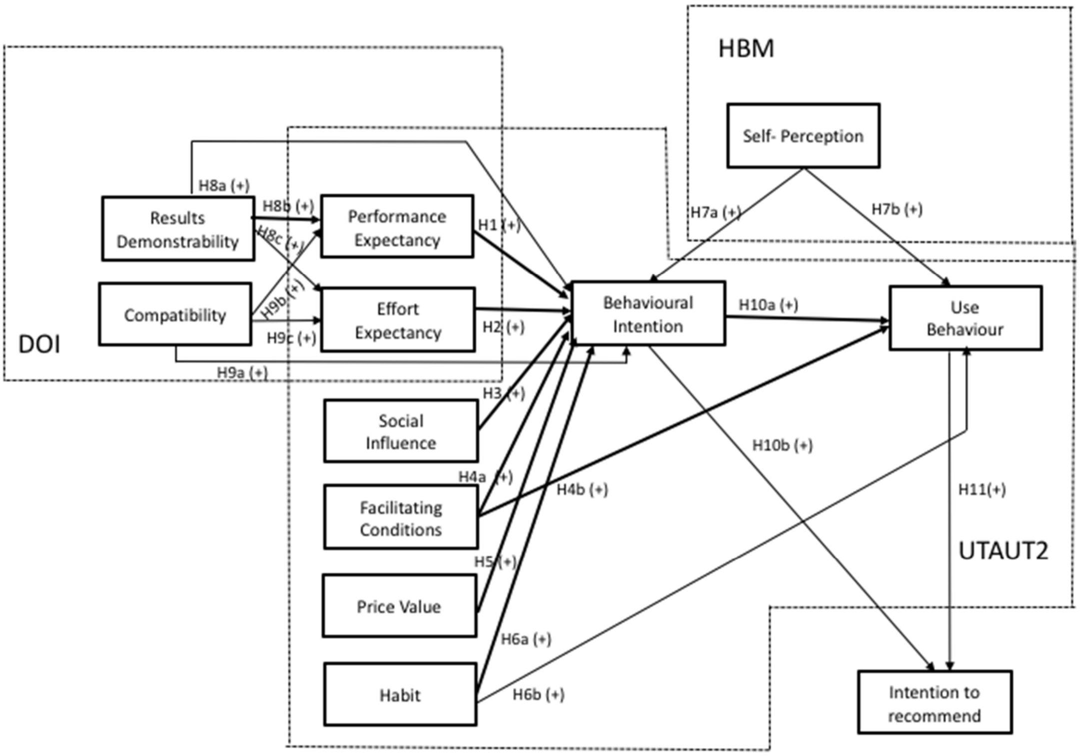


Figure 6.1 The Research Model

UTAUT2 Constructs

Performance expectancy is theorized to be the degree to which using a specific technology provides benefits to consumers in executing particular tasks (Venkatesh et al., 2003; Venkatesh et al., 2012). Overall, patients adopt and use more eHealth tools and EHR portals that provide benefits in executing on-line health related activities (Kim & Park, 2012; Tavares et al., in press; Tavares & Oliveira, 2016a; Wilson & Lankton, 2004)

H1. Performance expectancy will positively influence behavioural intention.

Effort expectancy is the degree of ease connected to consumers' usage of a certain technology (Venkatesh et al., 2003; Venkatesh et al., 2012) . The simpler it is for health care consumers to use an EHR Portal, the greater is the likelihood that they will use it (Kim & Park, 2012; Tavares et al., in press; Tavares & Oliveira, 2016a; Wilson & Lankton, 2004)

H2. Effort expectancy will positively influence behavioural intention.

Social influence is the extent to which people acknowledge that others who are significant to them believe they should use a particular technology (Kim & Park, 2012; Tavares & Oliveira, 2016a; Wilson & Lankton, 2004). According to the literature social influence plays a role in eHealth and EHR portals adoption, since patients with the same health issues tend to be induced by others sharing the same or similar condition (Bozan et al., 2015; Fisher & Clayton, 2012; Tavares & Oliveira, 2017; Thackeray et al., 2013).

H3. Social influence will positively influence behavioural intention.

Facilitating conditions refers to consumers' awareness of the support and resources available to execute a particular behaviour (Venkatesh et al., 2003; Venkatesh et al., 2012). A possible barrier to patients' use of eHealth tools is the non-existence of resources or support services that enable them to access and use these types of technology, implying that health care consumers with better conditions favour EHR portals usage and adoption (Keselman, et al., 2008; Tavares & Oliveira, 2017; Venkatesh et al., 2012).

H4(a). Facilitating conditions will positively influence behavioural intention.

H4(b) Facilitating conditions will positively influence use behaviour.

If we relate to consumer environment, price value is a relevant dimension, since consumers usually bear the costs linked with purchasing products and services (Venkatesh et al., 2012). If health care consumers can obtain their exams results online, for example through an EHR portal, they save time and transportation costs by avoiding an unnecessary trip to a clinic or hospital (Peek et al., 2014; Tavares & Oliveira, 2017).

H5. Price value will positively influence behavioural intention.

Habit can be described as the degree to which people tend to perform behaviours automatically due to learning (Venkatesh et al., 2012). According to recent literature, habit positively influences eHealth tools and EHR portals use and adoption (Tavares & Oliveira, 2017; Yuan et al., 2015).

H6(a). Habit will positively influence behavioural intention.

H6(b). Habit will positively influence use behaviour.

The role of behavioural intention has been recognized in eHealth, with the literature affirming that the driver of use and adoption of EHR portals is preceded by the behavioural intention to use them (Kim & Park, 2012; Tavares & Oliveira, 2016a, 2017; Wilson & Lankton, 2004).

H10(a). Behavioural intention will positively influence use behaviour.

Health Behaviour Construct

Supporting the concept of self-perception is the HBM. HBM assumes that subjective health concerns determine whether individuals execute a health-related action, such as making an appointment with their physician (Vandekar et al., 1992). Self-perception in health (Chan et al., 1998; Kaleta et al., 2009; Vandekar et al., 1992), posits that the perceived (rather than the real) severity of the health complaint could be the driving force inducing the action (Kaleta et al., 2009; Menec et al., 1999; Vandekar et al., 1992).

There is evidence in the literature that self-perception influences behavior intention to use eHealth tools and EHR portals (Kim & Park, 2012; Tavares & Oliveira, 2016a).

H7(a). Self-perception will positively influence behavioural intention

There is also evidence in the literature that self-perception, can not only drive intentions, but directly influences actions in the usage of health-related services (Kim & Park, 2012; Tavares & Oliveira, 2016a; Vandekar et al., 1992). Often with sensitive topics and particularly with health-related topics, mismatch between intentions and effective actions may occur (Angst & Agarwal, 2009; Baumgartner, 2006; Tavares & Oliveira, 2017). It is then also relevant to evaluate the potential positive effect of self-perception on use behaviour.

H7(b). Self-perception will positively influence use behaviour

DOI Constructs

Roger's (2003) DOI Theory is one of the most acknowledged theories for studying IT adoption (Zhang et al., 2015). According to DOI, innovation is an idea, technology or a process, that is perceived as unknown or new to a particular group of individuals (Rogers, 2003; Zhang et al., 2015). Diffusion is how the information about the innovation is shared inside the social system (Rogers, 2003). The attributes of an innovation comprise five user-perceived qualities: relative advantage, compatibility, complexity, trialability and observability (Rogers, 2003). Moore and Benbasat (1991) expanded the original set of innovation attributes proposed by DOI to be applicable to the IT setting. One example was the construct observability, which was subdivided in results demonstrability and visibility (Moore & Benbasat, 1991). Subsequent studies have found that results demonstrability is more relevant than visibility in predicting user intention to use a technology, and particularly in IT healthcare (Yi et al., 2006). We did not measure trialability, because there was no evidence that our target population has participated in a trial usage of EHR portals (Tavares & Oliveira, 2016b). EHR portals should be seen as new technology that relates to the concept of an innovation in consumer IT within the scope of health care.

Relative advantage is the extent to which the consumer perceives improvements or benefits upon the current technology by adopting an innovation (Rogers, 2003). Relative advantage measures fundamentally the same thing as performance expectancy within the context of DOI (Oliveira et al., 2016; Yi et al., 2006). Complexity measures the extent to which an innovation is difficult to understand or be used (Rogers, 2003). We also find a commonality between effort expectancy and complexity (Oliveira et al., 2016; Yi et al., 2006). Both relative advantage and complexity within the context of DOI, and according to the literature may be regarded as positively influencing the behavioural intention to adopt EHR portals (Tavares & Oliveira, 2016a, 2017; Yi et al., 2006; Zhang et al., 2015).

Results demonstrability is the degree to which the tangible results of adopting and using an innovation can be visible and then communicable (Moore & Benbasat, 1991). According to the literature this may have a direct effect on the behavioural intention to use an EHR Portal (Yi et al., 2006; Zhang et al., 2015). Also, potential users can better comprehend the benefits of using a new eHealth technology when noticeable results of the tool are directly evident, advocating a positive connection between results demonstrability and performance expectancy (Yi et al., 2006). The degree to which a specific individual noticed the results of using an innovation to be demonstrable, partially reflects belief in using the tool and more easily achieving the desired outcome (Yi et al., 2006; Zhang et al., 2015). Thus, we theorize and ground on the literature that result demonstrability will positively influence effort expectancy.

H8(a). Results demonstrability will positively influence behavioural intention

H8(b). Results demonstrability will positively influence performance expectancy

H8(c). Results demonstrability will positively influence effort expectancy

Compatibility measures the extent to which an innovation is perceived as being aligned with the existing consumer life style values and current and past experiences (Rogers, 2003). Compatibility has demonstrated to be a predictor of the behavioral intention to adopt a new technology in general, and also in consumer eHealth (Oliveira et al., 2016; Zhang et al., 2015), and also like results demonstrability as an antecedent of performance expectancy and effort expectancy (Oliveira et al., 2016; Zhang et al., 2015). Users may perceive EHR portals to be more compatible if they see advantages in using them to manage specific health care activities without additional complexity (Oliveira et al., 2016; Tavares & Oliveira, 2016a; Zhang et al., 2015). Compatibility consequently strengthens performance expectancy, effort expectancy, and behavioural intention to use EHR portals (Oliveira et al., 2016; Tavares & Oliveira, 2016a; Zhang et al., 2015).

H9(a). Compatibility will positively influence behavioural intention

H9(b). Compatibility will positively influence performance expectancy

H9(c). Compatibility will positively influence effort expectancy

Users' intention to recommend EHR portals

IT consumers with a greater intention to adopt a new technology are more likely to become users and to recommend that specific technology to others (Miltgen et al., 2013; Oliveira et al., 2016). Often with sensitive topics and particularly with health-related topics mismatch between intentions and effective actions may occur (Angst & Agarwal, 2009; Baumgartner, 2006; Tavares & Oliveira, 2017), so it is especially relevant to measure independently, how the behavioural intention and use behaviour may influence the intention to recommend the use of EHR portals.

H10(b). Behavioural intention will positively influence intention to recommend EHR portals to others.

H11. Use behaviour will positively influence intention to recommend EHR portals to others.

6.2 Methods

6.2.1 Measurement

All of the items were adopted from Venkatesh et al. (2012), Wilson and Lankton (2004), Vandekar et al. (1992), Moore and Benbasat (1991), and Oliveira et al. (2016), with minor changes in order to adapt to EHR Portal technology. The items are exhibited in Appendix 6.1. The questionnaire was delivered in Portuguese after being translated by a certified translator. To guarantee that the content did not lose its original meaning, a back-translation was made from Portuguese to English by a different certified translator, and compared to the original (Brislin, 1970). The scales' items were measured on a seven-point range 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 portal usage is not expected to be as regular as mobile Internet usage. Socio-demographic questions were also included. Age was measured in years and gender was coded as a dummy variable (0 or 1), with women represented by 0. Having a private health insurance was also coded as a dummy variable (0 or 1), with its absence represented by 0. Information about the level of education of the respondents was also assessed, with three different layers (university degree; high school education complete; high school education incomplete).

6.2.2 Data Collection

A pilot survey was performed to validate the questions and the scale of the survey. From the pilot survey, we had 20 responses. No issues were reported that could question the fact that the questionnaire items were not reliable. Still, from the outcome of the pilot survey there was strong evidence that our non-response rate in the main survey could be high (>50%). The data from the pilot survey were not included in the main survey. Because one of the goals of our study is to determine the usage prevalence rate of this type of technology, we sub-divided our survey into two phases. Two-phase sampling designs are frequently used in epidemiological studies, in health care, when a disease is rare and diagnosis of the disease is difficult or expensive (Gao, Hui, Hall, & Hendrie, 2000). In the first phase a bigger random sample from the targeted population is screened with less intensive and expensive screening. In the second stage a random sub-sample of the individuals is studied more intensively (Gao et al., 2000). We used a similar approach, our target population is also infrequent, but in our case the aim is to handle a potential high non-response rate. Specifically, our population of interest is the Portuguese adult population (age ≥ 18 years) who are users of EHR portals. In the first section, we asked the potential respondent if she/he was a Portuguese adult, if the response was positive, we asked if she/he was a user of EHR portals and only after (if she/he was a user), about her/his interest in replying to our main survey.

To interview our target population, we used a nationwide mobile phone survey. According to the latest research, 94.5% of the Portuguese adult population had a mobile phone by December 2016 (ANACOM, 2016), making it a valuable approach to conduct this survey due to its high coverage of the target population. The survey was computer assisted and all answers were immediately recorded. The mobile phone sample was comprised of randomly generated numbers. Portuguese mobile phone numbers are nine-digit and the first two digits identify the operator (ANACOM, 2016; Vicente & Reis, 2009). The Portuguese Telecommunications Regulation Authority (ANACOM) delivers information concerning the market share of the three operators offering mobile services in Portugal (ANACOM, 2016). This was used to split the sample into three mobile subsamples proportional to the market share (Aanerud, Braut, Wentzel-Larsen, Eagan, & Bakke, 2013; Picot et al., 2001; Vicente & Reis, 2009). Within each two-digit prefix of the three operators, numbers were created by a generator of 7 digit random numbers (Vicente & Reis, 2009). Up to additional four call attempts were made to each number in order to establish contact, with the exceptions when the number was identified as non-working or not attributed (a message from the operator provides this information) (Aanerud et al., 2013; Vicente & Reis, 2009). The survey took place between July 25th, 2017 and October 15th, 2017. All study participants were informed about the research purpose, confidentiality protection, and the anonymity of the information collected, and that by answering all the questions they were giving their consent to participate in the survey. In total, we obtained 15080 valid numbers. From this sample, we obtained a 71% response rate, regarding the question to identify the users of EHR portals. From the ones that were eligible to answer the survey we obtained 139 completed questionnaires, a response rate of 15.1% (see Figure 6.2).

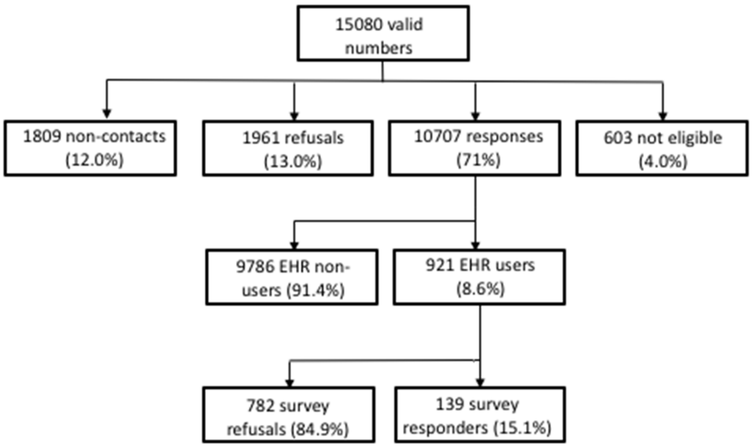


Figure 6.2 Sampling procedure and results

6.2.3 Data Analysis

To test our research model, we applied Partial Least Squares Structural Equation Modelling (PLS-SEM). The motivations for choosing this approach were the model complexity (many constructs and many indicators), formatively measured constructs are part of the structural model and the fact that the PLS-SEM method is oriented to explain variance of the research model and to detect statistically significant constructs (Hair et al., 2017; Hair et al., 2012; Ringle, Sarstedt, & Straub, 2012). SmartPLS 3 (Ringle, Wende, & Becker, 2015) was used to estimate the model. Before evaluating the structural model, we assessed the measurement model to evaluate construct reliability, indicator reliability, convergent validity, and discriminant validity.

6.3 Results

6.3.1 Sample Characteristics

The sample characteristics results *versus* the target population profile are displayed in Table 6. 2.

Table 6.2 Sample characteristics *versus* target population

	Sample (%)[b]	Population (%)[c]	
Age			*P <0.01*[a]
[18-34]	48.20	25.92	
[35-49]	41.70	27.35	
[50-64]	5.80	23.51	
≥65	4.30	23.22	
Gender			*P=0.814*[a]
Male	46.00	47.04	
Female	54.00	52.96	
Private Health Insurance			*P <0.01*[a]
Yes	56.00	25.10	
No	44.00	74.90	
Education			*P <0.01*[a]
University Degree	63.31	18.21	
Non- University Degree	36.69	81.79	

Notes:
1. [a] χ^2 test ;
2. [b] Sample size (n=139);
3. [c] Portuguese Census 2011 adult population (n= 8,657,240)

The age groups and the gender of the target population use as a source the latest Portuguese Census data from 2011 (INE, 2011), the level of education uses as a source the latest inquiry from the National Institute of Statistics in 2016 (Pordata, 2016), and, for the number of people with private health insurance in Portugal, the information from the Portuguese Association of Insurance Companies from 2016 (Mateus, Ramalho, Oliveira, Rodrigues, & Ferreira, 2017). Except with the case of gender, all other sample characteristics differ from the target population. We should not generalize these results as representative of the target population due to the high non-response rate in the second phase (Figure 6.2). Early adopters in eHealth are usually younger and more educated than the general population, in line with the findings of our study (Or & B.

Karsh, 2009; Ronda, Dijkhorst-Oei, Gorter, Beulens, & Rutten, 2013; Zhang et al., 2015). Higher income is also related with eHealth early adopters, which may justify the higher percentage of people in our sample compared with the target population, with private insurance (Or & Karsh, 2009; Zhang et al., 2015). In Portugal, there is a National Health System that provides coverage to all citizens, but there is a substantial increase in the last decade of people obtaining complementary private health insurance (Bohm et al., 2013; Jhamb et al., 2015; Mateus et al., 2017). In Portugal the main private health care institutions have also implemented measures to encourage the use of eHealth tools, including EHR portals (Tavares et al., in press).

We also assessed the common method variance (CMV) initially using Harman's one-factor test. If the total variance for a single factor is less than 50%, it suggests that CMV is not an issue (Podsakoff et al., 2003). The greatest variance explained by one factor, was 47.16%, in our case by the first one, still lower than 50%. Subsequently the marker-variable technique was applied, in which we used a theoretical unrelated construct, the marker variable (Lindell & Whitney, 2001). We found no significant correlation between the research model constructs and the marker variable. Therefore, we can conclude that CMV was not a serious problem, verified by two different and established criteria's (Lindell & Whitney, 2001; Malhotra et al., 2006; Podsakoff et al., 2003).

6.3.2 Usage Results

According to the results in the first stage of our inquiry, 8.6% of the Portuguese adult population uses EHR portals. This value is within the range of 5-10%, most commonly reported in the literature (Gheorghiu & Hagens, 2017; Tavares & Oliveira, 2016a). We obtained a response rate of 71% at the first stage. In the case of our survey we cannot assume that the non-responses are "missing at random," and hence their lack may lead to bias (Altman & Bland, 2007; Powney, Williamson, Kirkham, & Kolamunnage-Dona, 2014). According to the literature the ideal value for responses in a survey should be greater than or equal to 80%, to make assumptions about the results and if they are representative of the population (Altman & Bland, 2007; Evans, 1991). The types of non-responses in our survey are included in Figure 6.2. They include 4% of individuals who were non-eligible, mostly because their age was lower than 18 years. Overall and according to other surveys in general and surveys for populations of low prevalence, our response rate may be regarded as reasonable (Aanerud et al., 2013; Kalton & Anderson, 1986; Picot et al., 2001; Vicente & Reis, 2009).

Table 6.3 EHR portals usage patterns

	Average	Median	Minimum	Maximum
UB1	4.37	5.00	1.00	7.00
UB2	4.75	5.00	1.00	7.00
UB3	4.56	5.00	1.00	7.00
UB4	3.34	3.00	1.00	7.00

Notes:

1. UB1: Management of personal information and communication with health providers; UB2: Medical appointments schedule; UB3: Check their own EHR; UB4: Request for medical prescription renewals

The usage patterns reported in Table 6.3 show a good adoption and usage by the users. The feature with the least usage is the request for medical prescription renewals; our sample is relatively young (mean age=36.0 years). The request for prescription renewals is usually related with chronic conditions that are more prevalent amongst older people (Osborn et al., 2013; Tavares & Oliveira, 2016b).

6.3.3 Measurement Model

Typically, the first criterion to be assessed is construct reliability or internal consistency reliability. It is traditionally evaluated by Cronbach's alpha, which delivers an estimation of the reliability grounded on the intercorrelations of the observed indicator variables (Hair et al., 2017). Cronbach's alpha assumes that all indicators are equally reliable. However PLS-SEM prioritizes the indicators according to their individual reliability (Hair et al., 2017). Due to Cronbach's alpha stated limitations, it is technically more suitable to apply an alternative measure for the same purpose, which is mentioned to as composite reliability (Hair et al., 2017). The Composite reliability measure takes into account the different indicator variable's outer loadings (Hair et al., 2017). Table 6.4 shows that all constructs have composite reliability higher than 0.70, showing evidence of internal consistency (Venkatesh et al., 2012).

Table 6.4 Cronbach's alpha, composite reliability, and average variance extracted (AVE)

	Cronbach's Alpha	Composite Reliability	AVE
Behavioural Intention	0.93	0.95	0.88
Compatibility	0.94	0.95	0.84
Effort Expectancy	0.89	0.93	0.78
Facilitating Condition	0.82	0.88	0.66
Habit	0.88	0.92	0.80
Intention to Recommend	0.88	0.94	0.89
Performance Expectancy	0.86	0.92	0.79
Price Value	0.95	0.97	0.92
Results Demonstrability	0.88	0.93	0.81
Social Influence	0.96	0.97	0.92
Self-Perception	0.82	0.89	0.74

The most commonly used PLS-SEM measure to access convergent validity on the construct level is the average variance extracted (AVE) (Hair et al., 2017; Hair et al., 2012). According to the literature we should aim to an AVE value of 0.50 or greater, meaning that on average the construct explains more than 50% of the variance of its indicators (Hair et al., 2017; Hair et al., 2012). The results in Table 6.4 demonstrate that this criterion is fully achieved. Also to evaluate indicator reliability, a well-known role of thumb is that a latent variable should explain a significant part of each indicator's variance, ideally at least half (Hair et al., 2017; Hair et al., 2011). This means that an indicator's outer loading should be greater than or equal to 0.70 (Hair et al., 2017; Hair et al., 2011). Nevertheless, indicators with outer loadings between 0.40 and 0.70 should be removed only when deleting the indicators leads to an increase in the AVE or the composite reliability above the suggested threshold value (Hair et al., 2017; Hair et al., 2012). Only one indicator was removed SP4, with an outer loading below 0.4. All other indicators have an outer loading higher than 0.7 and are shown in Appendix 6.2.

Table 6.5 Correlations and square roots of AVEs

	BI	CO	EE	FC	HT	IR	PE	PV	RD	SI	SP	UB
BI	**0.94**											
CO	0.81	**0.92**										
EE	0.56	0.65	**0.88**									
FC	0.61	0.64	0.67	**0.81**								
HT	0.70	0.62	0.54	0.53	**0.90**							
IR	0.83	0.78	0.61	0.59	0.59	**0.94**						
PE	0.69	0.65	0.48	0.47	0.54	0.65	**0.89**					
PV	0.55	0.58	0.51	0.41	0.68	0.54	0.46	**0.96**				
RD	0.62	0.76	0.66	0.58	0.56	0.64	0.53	0.52	**0.90**			
SI	0.49	0.42	0.42	0.32	0.57	0.49	0.49	0.41	0.37	**0.96**		
SP	0.51	0.43	0.22	0.33	0.55	0.40	0.49	0.24	0.45	0.38	**0.86**	
UB	0.68	0.57	0.49	0.49	0.72	0.63	0.55	0.52	0.51	0.53	0.60	F

Notes:

1. BI: Behavioural intention; CO: Compatibility; EE: Effort expectancy; FC: Facilitating conditions; HT: Habit; IR: Intention to recommend; PE: Performance expectancy; PV: Price value; RD: Results demonstrability; SI: Social influence; SP: Self- perception; UB: Use behaviour; F: Formative construct
2. Diagonal elements are square roots of AVEs
3. Off-diagonal elements are correlations.

Discriminant validity is the degree to which a construct is truly dissimilar from the other constructs in the model (Hair et al., 2017). Traditionally, researchers have relied on two measures of discriminant validity (Hair et al., 2017; Hair et al., 2012). One is the Fornell-Larcker criterion, which compares the square root of the AVE values with the latent variables' correlations. Particularly, the square root of each construct's AVE should be bigger than its highest correlation with any other construct (Hair et al., 2017; Hair et al., 2012), and as seen in Table 6.5 this criterion is met. The other traditional measure of discriminant validity is the cross-loadings. Particularly, an indicator's outer loading on the associated construct should be higher than any of its cross-loadings on other constructs (Hair et al., 2017; Hair et al., 2012). This criterion is also met, as seen in Appendix 6.2. Recent research suggests the use of an alternative criterion, the heterotrait-monotrait ratio (HTMT) of the correlations. HTMT is the ratio of the between-trait correlations to the within- trait correlation (Hair et al., 2017). Ideally the HTMT value should be different from 1; prior research suggests a threshold value of 0.90 (Hair et al., 2017). Ideally, to avoid any ambiguity, the most recent research applied a procedure called bootstrapping to derive a distribution of the HTMT statistic and to determine if it is significantly different from 1 (Hair et al., 2017). With this procedure it is feasible to derive a bootstrap confidence interval (e.g., 95%). A confidence interval including the value 1 indicates a lack of discriminant validity. To the contrary, if the value 1 falls outside the interval's range, this advocates that the two constructs are empirically different (Hair et al., 2017). This criterion is also met for our model, as seen in Appendix 6.2.

Use behaviour, which was modelled using four formative indicators, is evaluated by specific quality criteria linked with formative indicators (Hair et al., 2017). A recently proposed way to evaluate the formative construct's validity is to examine its correlation with an alternative measure of the construct, using a global single item or reflective measures (redundancy analysis). The strength of the path coefficients linking the two constructs should be at least of 0.70 (Hair et al., 2017). In our study we used a global single item for use behaviour, obtaining a path coefficient of 0.851, thus confirming the convergent validity for the use behaviour formatively measured construct. Additionally, we need to assess the formative indicators for potential collinearity issues. As seen in Table 6.6, all variance inflation factors are below 5, meaning that collinearity is not an issue (Hair et al., 2017). An additional relevant criterion for evaluating the contribution of a formative indicator is its weight to be statistically significant, or in case they are not significant its outer loading must be greater than 0.5 (Hair et al., 2017). All formative indicators comply with these assumptions, as shown in Table 6.6.

Table 6.6 Formative indicators' quality criteria

Indicators	**VIF**	***t* value (weights)**	**Outer Loadings**
UB1	1.98	4.92**	0.89
UB2	2.43	4.48**	0.86
UB3	3.40	0.75	0.80
UB4	1.57	1.79	0.66

Notes:

1. VIF: Variance inflation factor;
2. ** $P < 0.01$; * $P < 0.05$;
3. UB1= Management of personal information and communication with health providers; UB2= Medical appointments schedule; UB3=Check their own EHR; UB4= Request for medical prescription renewals

Considering all the results and findings, all reflective and formative constructs exhibit satisfactory levels of quality. Thus, we can proceed with the evaluation of the structural model.

6.3.4 Structural Model

Structural model path significance levels were estimated using a bootstrap with 5000 iterations of resampling to obtain the maximum possible consistency in the results (Hair et al., 2017). We checked the structural model for collinearity issues by examining the VIF values of all sets of predictor constructs and all VIF values are below the threshold of 5. Therefore, collinearity is not a critical issue in the structural model (Hair et al., 2017). To assess the structural model we used the R^2, path coefficients significance and the f^2 effect size (Hair et al., 2017; Hair et al., 2012).The results are shown in Table 6.7. Overall the model explains 76.0% of the variance in behavioural intention and 61.8% in use behaviour, being these two the most relevant dependent variables in our model. In addition to assessing the R^2 values of all endogenous constructs, the change in the R^2 value when a specific construct is removed from our model can be used to assess whether the construct has a substantial impact on the endogenous constructs (Hair et al., 2017). Guidelines for measuring f^2 are that values of 0.02, 0.15, and 0.35, respectively, represent small, medium, and large effects of the exogenous latent variable; values of less than 0.02 denote that there is a null effect (Hair et al., 2017). Taking a particularly important role in our model, compatibility has a medium effect on both behavioural intention and performance expectancy and a small effect on effort expectancy, showing the relevance of this construct in our research model. Another construct with a relevant role in our model is behavioural intention, with a large effect on intention to recommend and a small effect on use behaviour. Finally, habit is a construct that has a medium effect size on use behaviour and a small effect size on behavioural intention. With only small effect sizes we have the effect of performance expectancy on behavioural intention, self-perception on use behaviour, results demonstrability on effort expectancy, and use behaviour on intention to recommend, but this last one without a statistically significant path coefficient.

Table 6.7 Structural model results and findings regarding Hypotheses

Dependent variables[a]	Independent variables[a]	$f^{2\,b}$	$\hat{\beta}$	$t_{\beta}{}^{c}$	Hypothesis	Results	R^2	R^2_{adj}
BI							0.760	0.743
	PE	0.081	0.203	2.699**	H1	Supported		
	EE	0.001	-0.022	0.311	H2	Not Supported		
	SI	0.002	0.025	0.450	H3	Not Supported		
	FC	0.014	0.086	1.547	H4(a)	Not Supported		
	PV	0.000	-0.015	0.277	H5	Not Supported		
	HT	0.079	0.251	2.660**	H6(a)	Supported		
	SP	0.008	0.062	0.916	H7(a)	Not Supported		
	RD	0.015	-0.102	1.357	H8(a)	Not Supported		
	CO	0.328	0.530	6.189**	H9(a)	Supported		
UB							0.618	0.607
	FC	0.005	0.056	0.727	H4(b)	Not Supported		
	HT	0.165	0.378	3.821**	H6(b)	Supported		
	SP	0.095	0.233	2.971**	H7(b)	Supported		
	BI	0.075	0.263	2.379*	H10(a)	Supported		
IR							0.690	0.685
	BI	0.962	0.747	10.737**	H10(b)	Supported		
	UB	0.023	0.116	1.565	H11	Not Supported		
EE							0.483	0.476
	CO	0.092	0.337	2.243*	H9(c)	Supported		
	RD	0.131	0.403	2.888**	H8(c)	Supported		
PE							0.427	0.418
	CO	0.257	0.594	6.141**	H9(b)	Supported		
	RD	0.004	0.075	0.561	H8(b)	Not Supported		

Notes:

1. [a] BI: Behavioural intention; CO: Compatibility; EE: Effort expectancy; FC: Facilitating conditions; HT: Habit; IR: Intention to recommend; PE: Performance expectancy; PV: Price value; RD: Results demonstrability; SI: Social influence; SP: Self- perception; UB: Use behaviour
2. [b] ** $P < 0.01$; * $P < 0.05$
3. [c] [0.02-0.15[= small effect; [0.15-0.35[= medium effect; ≥0.35 = large effect

6.4 Discussion

6.4.1 Principal Findings

The results advocate that using our new research model in an eHealth-related area—EHR Portal acceptance by patients—yields very good results, explaining 76.0% of the variance on behavioural intention and 61.8% of the variance in use behaviour, the most relevant dependent variables in our model (Venkatesh et al., 2012). We also obtained an R^2 of 69.0% in intention to recommend, also a very good result (Oliveira et al., 2016; Venkatesh et al., 2012). Overall the use of the three theories, UTAUT2, HBM, and DOI, was a successful strategy because in all of them we had constructs with statistically significant impact on explaining the adoption of EHR portals (see Figure 6.3). The constructs with highest effect size in the model were compatibility, habit, and behavioural intention.

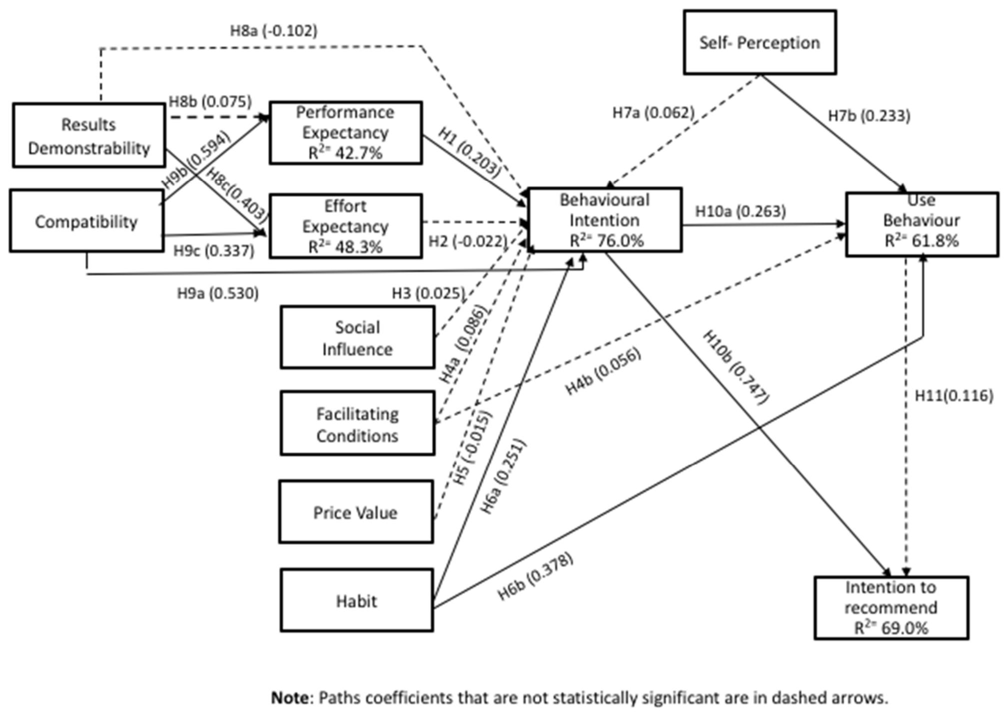


Figure 6.3 Structural model results

6.4.2 Theoretical Implications

In our model performance expectancy has a statistically significant effect on behavioural intention, suggesting that individuals care about the results and advantages that EHR portals can bring for them to manage their own health more effectively, supporting H1. This finding is supported by previous studies (Tavares & Oliveira, 2017; Wilson & Lankton, 2004). In regard to effort expectancy there is no statistically significant impact, not supporting H2. This finding contradicts results from earlier studies that used effort expectancy as part of UTAUT2 (Tavares et al., in press; Tavares & Oliveira, 2016a), but in other studies also with new technologies and within healthcare, when effort expectancy is evaluated as part of DOI, it also obtained non-significant results (Oliveira et al., 2016; Yi et al., 2006). A possible explanation also supported by the literature is that early adopters of new technologies have a higher cognitive ability and are more used to manage complexity, and that they do not perceive it as an obstacle to use EHR portals (Rogers, 2003; Yi et al., 2006).

In our research model, social influence did not show a statistically significant effect on behavioural intention, thus not supporting H3. Previous studies have shown potential differences, with results differing amongst countries, with its positive significance being more consistent in US (Bozan et al., 2015; Tavares et al., in press; Tavares & Oliveira, 2016a, 2017). Potential cultural differences may explain the different behaviours. In our study, our early adopters of EHR portals seem to be more driven by their own individual willingness to try a new technology than to be influenced by what the society generally do. This is also an assumption supported by DOI theory (Rogers, 2003). The non-confirmation of the facilitating conditions hypothesis, H4(a) and H4(b), advocates that the individuals in our study believe that the resources or know-how to use EHR portals are not an issue. This can be justified by the ability of having access to a computer and the Internet and is aligned with recent literature findings (Tavares & Oliveira, 2016a; Yuan et al., 2015). H5 was rejected. In Europe, access to most of the eHealth services are free of charge, so the value that is provided to the patients is to permit them to execute specific activities more efficiently online. Regrettably, that fact seems not to be acknowledge by the patients. Habit has a statistically significant impact on both behavioural intention and use behaviour supporting both H6(a) and H6(b). Habit is a consumer specific construct with a very significant role in our model, showing how important it is to have models tailored with consumer specific constructs and not just general IT adoption constructs (Venkatesh et al., 2012), and is also supported by recent literature findings (Tavares & Oliveira, 2017; Venkatesh et al., 2012; Yuan et al., 2015).

Self-perception has a statistically significant impact on use behaviour supporting H7(b) and a non-significant impact on behavioural intention H7(a). Often with sensitive topics and particularly with health-related topics, mismatch between intentions and effective actions occur (Angst & Agarwal, 2009; Baumgartner, 2006; Tavares & Oliveira, 2017). In fact, this is the case with self-perception. Although it does not drive the intentions, self- perception directly influences actions, in the usage of EHR portals. Results demonstrability has a statistically significant impact on effort expectancy supporting H8(c) and a non-significant impact on both performance expectancy H8(b) and behavioural intention H8(a), not supporting these two last hypotheses. Our results point out that when an innovation produces results that are readily discernible, perceptions of how easy it is to use a technology are considerably affected (this finding is in line with the literature (Yi et al., 2006)), but not the perceptions related with performance expectancy or a direct influence on behavioural intention. Compared with results demonstrability, also from DOI, compatibility has a much greater effect in our research model demonstrated not only by the f^2 but also by having all its paths in the model statistically significant. Compatibility has a statistically significant impact on behavioural intention H9(a), performance expectancy H9(b), and effort expectancy H9(c), supporting these three hypotheses. The results indicate that behavioural intention H9(a), performance expectancy H9(b), and effort expectancy H9(c) are greater when the health care consumer perceives the technology to be compatible. Our study's results are in line with other studies in this regard (Yi et al., 2006; Zhang et al., 2015). Behavioural intention positively influences use behaviour, supporting H10(a). This finding is in line with the literature suggesting that using EHR portals and eHealth tools is preceded by the intention to use them (Kim & Park, 2012; Tavares & Oliveira, 2017; Venkatesh et al., 2012; Yuan et al., 2015). Behavioural intention also positively influences intention to recommend, supporting H10(b). Our model explains 69.0% of the variance in recommendation, and the findings validate the significant influence of behavioural intention over it. Nevertheless, use behaviour does not have a significant impact on intention to recommend, not supporting H11. A probable explanation might be that being a high user does not necessarily link to higher recommendation, but that a strong intention to use, independently of the usage level, is a stronger predictor of intention to recommend.

6.4.3 Managerial Implications

The study identifies areas that may influence EHR Portal adoption, regarding its conceptualization, implementation and re-design. Performance expectancy is a significant adoption driver of EHR portals. So, when conceiving and promoting EHR portals, it is relevant to emphasize the advantages that they provide to the users in managing their health-related activities more efficiently. It is also important when conceiving an EHR Portal that results are easily demonstrable because perceptions of how easy a technology is to use are affected by them. Compatibility is a very important construct in our model and it is important to develop EHR portals that fit the health care customer's life style. A good example is the providers that are already developing mobile versions of their EHR portals, allowing people to access their data everywhere (Tavares et al., in press). In addition to the automatic and direct effect of habit on usage, habit also operates as a stored intention path to influence behaviour (Venkatesh et al., 2012). This requires more communication effort to reinforce both the stored intention and its link to behaviour (Venkatesh et al., 2012). Because habit has been defined as the degree to which individuals tend to execute behaviours automatically due to learning (Venkatesh et al., 2012), it is advisable that EHR portals have customer support services to help and provide support to the users with the platform.

Another relevant outcome is that the construct that is specific to health care—self-perception—also has a statistically significant role on the EHR portals usage. Self-perception is linked to the fact that the perceived, rather than the real, severity of the health problem is the driving force behind the action (Vandekar et al., 1992). Health care interventions that enable the patient to be more conscious of her/his health condition(s) may also endorse the usage of the EHR Portal. Also, the inclusion of educational health materials in the EHR portals may encourage patients to use the platform. Another important contribution of our study is to be able to demonstrate the influence of the intention to recommend in the adoption of EHR portals. Social network marketing, opinions shared by friends and relatives, are influential ways to help in the promotion and successful adoption of EHR portals. The managerial implications stated here are relevant not only for enhancing the adoption of EHR portals, but also for growing the usage frequency of current users. These can be done by developing new EHR portals or by making improvements to existing ones.

6.4.4 Limitations and Future Research

Unfortunately, our study had a very high non-response rate concerning people that refused to answer the main questionnaire. With this high non-response rate it is difficult to make direct assumptions related with the users in the Portuguese population. Nevertheless, earlier literature indicates that users and early users of eHealth tools and EHR portals are younger and more educated than the population average (Or & Karsh, 2009; Ronda et al., 2013; Tavares & Oliveira, 2016a, 2017; Zhang et al., 2015), in line with our study findings. The use of SEM is usually linked with the need of having questionnaires that are not short, making it more difficult for people to answer this questionnaire, especially by phone (Hair et al., 2017; Hair et al., 2011; Vicente & Reis, 2009). The use of gifts and other incentives may be a useful strategy to overcome the issue of the high non-response rate (Venkatesh et al., 2012). Testing the research model with samples of EHR portals users from other countries may also be an interesting path to follow, since the literature has shown that multi-country assessment provides interesting and diverse insights (Andreassen et al., 2007; Hoque et al., 2017; Tavares & Oliveira, 2017). We used PLS-SEM instead of CB-SEM, for the following reasons (Hair et al., 2017; Hair et al., 2011): we have a complex model (many constructs and many indicators), we had the goal of identifying key “driver” constructs, and we also verified that our data were nonnormaly distributed. We acknowledge that future research may go in the direction of using CB-SEM, which allows using global goodness-of-fit criterions, but due to the circumstances and the study goals, we adopted PLS-SEM, in our research (Hair et al., 2017; Hair et al., 2011).

6.5 Conclusion

Although acknowledging that we had a very high non-response rate at the second phase of our sampling procedure, the much lower non-response rate at the first phase provides an estimate of 8.6% usage of these types of platforms in Portugal, a valuable contribution from our study. Our respondents demographics follow the same trend as reported in other similar studies in the literature (Or & Karsh, 2009; Ronda et al., 2013; Zhang et al., 2015), providing additional support to our findings. Overall the use of the three theories, UTAUT2, HBM, and DOI, to support our research was a successful strategy because in all of them we had constructs with statistically significant impact on explaining the adoption of EHR portals. We were also able to demonstrate that consumers with a greater intention to adopt a new technology are more likely to become users and to recommend that specific technology to others. The new research model obtained very good results, with relevant R^2 in the most important dependent variables that help to explain the adoption of EHR portals, behavioural intention (76.0%) and use behaviour (61.8%).

Chapter 7- Conclusions

7.1 Principal Findings

EHR portals are a very important technology that give patients access to medical records and services such as appointment scheduling, notification systems, and e-mail access to the health care provider (Andreassen et al., 2007; Angst & Agarwal, 2009; Tavares & Oliveira, 2014b; Weingart et al., 2006). EHR portals have received great attention at governmental level worldwide, being perceived as a technology approach that brings significant benefits for both patients and health care providers (Blumenthal & Tavenner, 2010; Tavares & Oliveira, 2016b). In the US, the federal government via the meaningful use program committed significant resources to support the adoption and usage of EHRs through incentive payments adding up to $27 billion over a 10 years period (Blumenthal & Tavenner, 2010). In Europe a trans-European initiative, the European Patients Smart Open Services (epSOS). EpSOS focused on developing a practical eHealth framework and ICT infrastructure that enables secure access to patient health information amongst different European health care systems (Tavares & Oliveira, 2016b). Understanding the acceptance and use of eHealth technology by health care consumers it is a very relevant topic, particularly when in most countries there is still a low level of adoption of this technology (Gheorghiu & Hagens, 2017).

According to the literature review, there is still a lack of studies that address the topic of understanding why people adopt and use EHR portals, making this a topic that needs more empirical research. According to the findings in the literature review the complexity surrounding EHR portals demands having a patient-centred model that should be able to cover additional dimensions related with the health behaviour, confidentiality concerns, and innovation drivers. Potential adoption differences between countries with different regulations and different health care models should also be tested. In this dissertation with empirical studies, we used a research path that enables us to test these assumptions.

In Chapter 3 we tested UTAUT2 to evaluate the feasibility and results obtained with this consumer-centred model in regard to EHR Portal adoption. We collected a particularly large sample of responses *(n=386)* via an online survey. We found that performance expectancy, effort expectancy, social influence, and habit are statistically significant drivers of behavioural intention and that habit and behavioural intention are statistically significant drivers of use. The model explained 52% of the variance in behavioural intention and 31% of the variance in technology use, in line with R^2 obtained in other studies covering the same topic (Angst & Agarwal, 2009). With the majority of the constructs having a significant impact and with habit a consumer specific construct from UTAUT2 having the most relevant impact in both behavioural intention and use, UTAUT2 showed its importance as a consumer-centred model predicting the factors that drive health care consumers to use EHR portals. Nevertheless, the effect of moderation (age and gender), in most of the cases did not show a statistically significant impact when studying EHR portals adoption.

In Chapter 4 we added to the UTAUT2 a new construct derived from the HBM, providing an extension to the UTAUT2 with a health related potential driver, since EHR portals are an eHealth tool. We collected 360 responses via an online survey. We found that performance expectancy, effort expectancy, habit and self-perception are statistically significant drivers of behavioural intention and that habit, and behavioural intention are statistically significant drivers of use behaviour. The model explained 49.7% of the variance in behavioural intention and 26.8% of the variance in use behaviour in line with R^2 obtained in other studies covering the same topic (Angst & Agarwal, 2009). Self- perception, a health-related construct showed, its importance, by being a statistically significant predictor of behavioural intention, demonstrating the usefulness of including a construct derived from the HBM in a technology applied in the field of health care. We also included a new moderator, chronic disability (e.g. patients with a chronic disease or disability), also related with the health care field, postulating that patients with a chronic disease are more likely to adopt EHR portals if they have the resources and support available (i.e. facilitating conditions). Although this hypothesis was pointed out by the literature we were not able to support it in our study. Also, the other moderators (age and gender) did not reveal to have a relevant moderation effect in our study.

In Chapter 5 we combined UTAUT2 with the CFIP framework and performed a cross-country analysis between Portugal and the US. US and Portugal represent different health care models, regarding not only the support and coverage that each of them provide to their patients, but also regarding the health data privacy regulations (Angst & Agarwal, 2009; Bohm et al., 2013; Milberg et al., 2000). According to these countries health care systems differences, both UTAUT2 and CFIP provide the constructs and theoretical background to access potential differences between the two countries in what matters in the adoption of EHR portals. If we look into the fact that in the US there is no NHS and the patients need to have an expensive private insurance or pay directly to the health care provider to have health care support and that in Portugal there is universal health coverage (Bohm et al., 2013), it is postulated that the value that the US citizens give to a tool like EHR portals may be greater than what the Portuguese citizens give. This was measured by the UTAUT2 price value construct. It should also be expected that confidentiality concerns in US are greater than in Portugal, due to the less strict regulation in US regarding patient data confidentiality (Angst & Agarwal, 2009; Milberg et al., 2000). This was measured by the CFIP framework. In this study, an online questionnaire was administrated in the US and in Portugal. We collected a total of 597 valid responses. The statistically significant factors of behavioural intention in the global model (including the US and Portugal) are performance expectancy, effort expectancy, social influence, hedonic motivation (with a negative effect), price value, and habit. The predictors of use behaviour in the global model are habit and behavioural intention. Social influence, hedonic motivation, and price value are predictors only in the US group. Regarding the price-value construct statistically significant differences were found between the US and Portugal, as expected. It was also found that EHR portals usage patterns are significantly higher in the US compared to Portugal. Confidentiality issues do not seem to influence acceptance, neither in the global model or in the single country models, nor are there statistically significant differences between Portugal and the US. It seems that when someone starts using an EHR Portal, the impact of confidentiality concerns on effective use is not significant. It seems that when a patient overcomes the barrier of potential intention to use, to effective opt-in use of an EHR Portal, confidentiality concerns, measured via CFIP in our study are no longer a significant obstacle. There is evidence in the literature that with positive argumentation about EHR portals, confidentiality concerns will no longer significantly impact adoption (Angst & Agarwal, 2009). There is recent literature about the on-going implementation of meaningful use that seems to support this evidence and that there is a higher trust in healthcare care institutions and less privacy concerns than before (Ancker, Brenner, et al., 2015; Mackert et al., 2016). The global model explained 53% of the variance in behavioural intention and 36% of the variance in use behaviour, with these values higher in the US group, 64% on behavioural intention and 47% on use behaviour. With this study we verified the importance to perform cross-country evaluations when studying EHR portals adoption.

In Chapter 6 we presented a new research model with constructs from UTAUT2, HBM, and DOI. The new research model results from a detailed literature review about our study topic and also from the findings from previous empirical research presented in the previous chapters of this dissertation. From UTAUT2 we included all constructs except hedonic motivation. During previous empirical research, hedonic motivation was shown not to be an efficient predictor of the intention to adopt EHR Portals. In fact, hedonic motivation is defined as pleasure or enjoyment.

Using an EHR portal when someone is sick, it is most probably not an act of enjoyment but instead a need. The HBM and the self-perception construct are a much better concept about the motivations that may lead people to use EHR portals. The DOI theory was also incorporated in our research through the innovation attributes, except trialability, which we did not tested because there was no evidence that our sample was involved in a trial or test period of an EHR Portal. We collected a total of 139 valid responses from a national survey based on randomly generated mobile phone numbers. We used a two-phase sampling approach. In the first phase, we inquired the potential respondent if she/he was a Portuguese adult; if the response was positive, we would inquire if she/he was a user of EHR portals, and only then, about her/his interest in replying to our main survey. From this sample, we obtained a 71% response rate, regarding the question to identify the users of EHR portals, with 8.6% usage prevalence in the adult Portuguese population, a significant contribution from our study. Performance expectancy, compatibility, and habit have a statistically significant impact in behavioural intention (R^2= 76.0%). Habit, self-perception and behavioural intention have a statistically significant impact on use behaviour (R^2= 61.8%). Additionally, behavioural intention has a statistically significant impact on intention to recommend (R^2= 69.0%). Compatibility from DOI demonstrated to be one of the constructs with the greatest impact in our new research model, showing the value of including DOI constructs in our model (Angst & Agarwal, 2009; Venkatesh et al., 2012). Overall, the new model brings significant contributions from UTAUT2, HBM and DOI to explain EHR portals adoption, yielding very good results, explaining 76.0% of the variance on behavioural intention and 61.8% in use behaviour. Below Table 7.1 presents a summary of the results obtained with the different empirical results presented in this dissertation, which supported the conceptualization of the final research model.

Table 7.1 Constructs with significant results obtained in this dissertation's empirical studies

Constructs		Study 1 (Chapter 3)	Study 2 (Chapter 4)	Study 3 (Chapter 5)	Study 4 (Chapter 6)
BI [f]					
	PE[a,d]	Yes	Yes	Global: Yes US: Yes PT: Yes	Yes
	EE[a,d]	Yes	Yes	Global: Yes US: Yes PT: Yes	No
	SI[a]	Yes	No	Global: Yes US: Yes PT: No	No
	FC[a]	No	No	Global: No US: Yes PT: No	No
	HT[b]	Yes	Yes	Global: Yes US: Yes PT: Yes	Yes
	HM[b]	No	No	Global: Yes US: Yes PT: No	NT
	PV[b]	No	No	Global: Yes US: Yes PT: No	No
	SP[c]	NT	Yes	NT	No
	CO[d]	NT	NT	NT	Yes
	RD[d]	NT	NT	NT	No
UB [f]					
	BI[a]	Yes	Yes	Global: Yes US: Yes PT: Yes	Yes
	FC[a]	No	No	Global: No US: No PT: Yes	No
	HT[b]	Yes	Yes	Global: Yes US: Yes PT: Yes	Yes
	SP[c]	NT	NT	NT	Yes
	CL[e]	NT	NT	Global: No US: No PT: No	NT
	ER[e]	NT	NT	Global: No US: Yes PT: No	NT
	SU[e]	NT	NT	Global: No US: No PT: No	NT
	UA[e]	NT	NT	Global: No US: No PT: No	NT

Notes:

1. Yes: $P< 0.05$; No: $P>0.05$; NT: not tested in the study.
2. BI: Behavioural intention; CL: Collection; CO: Compatibility; EE: Effort expectancy; ER: Errors; FC: Facilitating conditions; HM: Hedonic motivation; HT: Habit; PE: Performance expectancy; PV: Price value; RD: Results demonstrability; SI: Social influence; SP: Self- perception; SU: Secondary use; UA: Unauthorized access; UB: Use behaviour.
3. [a] general IT adoption constructs; [b] IT consumer specific constructs; [c] health related construct; [d] DOI constructs; [e] Confidentiality (CFIP) constructs; [f] dependent variables.

Figure 7.1 shows the final research model, in which we see that all three theories/models bring a relevant contribution to the understanding of EHR Portal adoption. We did not use moderators in the final model due to the low impact that they have shown in the previous empirical research in this dissertation. The fact that we have a group of early users, younger than the population average and more educated, make them a more homogeneous group, making it more difficult for moderators to reveal differences that can produce impact (Hair et al., 2017). These socio-demographic characteristics mentioned in the literature were also revealed by our empirical research, being particularly relevant the findings from the latest empirical research (Chapter 6). If the use of the moderators did not provide significant findings, the multi-group analysis approach testing two countries with different health care models, showed differences (Chapter 5). Probably the most relevant finding is that the price value construct was never significant in the samples targeting the Portuguese population (see Table 7.1), but was significant in the US sample. Also looking to Figure 7.1 we can realize that the social influence construct did not have a statistically significant impact in the final research model. But looking to Table 7.1, we confirm that in two previous studies including the US sample the construct had a significant impact. We can conclude that it is relevant to have a line of research and a model that is able to cover different countries and environments, as we did. It is true that we could have attempted to test it all in one single model (e.g. moderators, cross-country analysis) but that would have made it too complex to be parsimonious and applicable (Hair et al., 2017), and it would also turn it to be a very long questionnaire, which is not good if you want to have survey responders committed to answer the questionnaire.

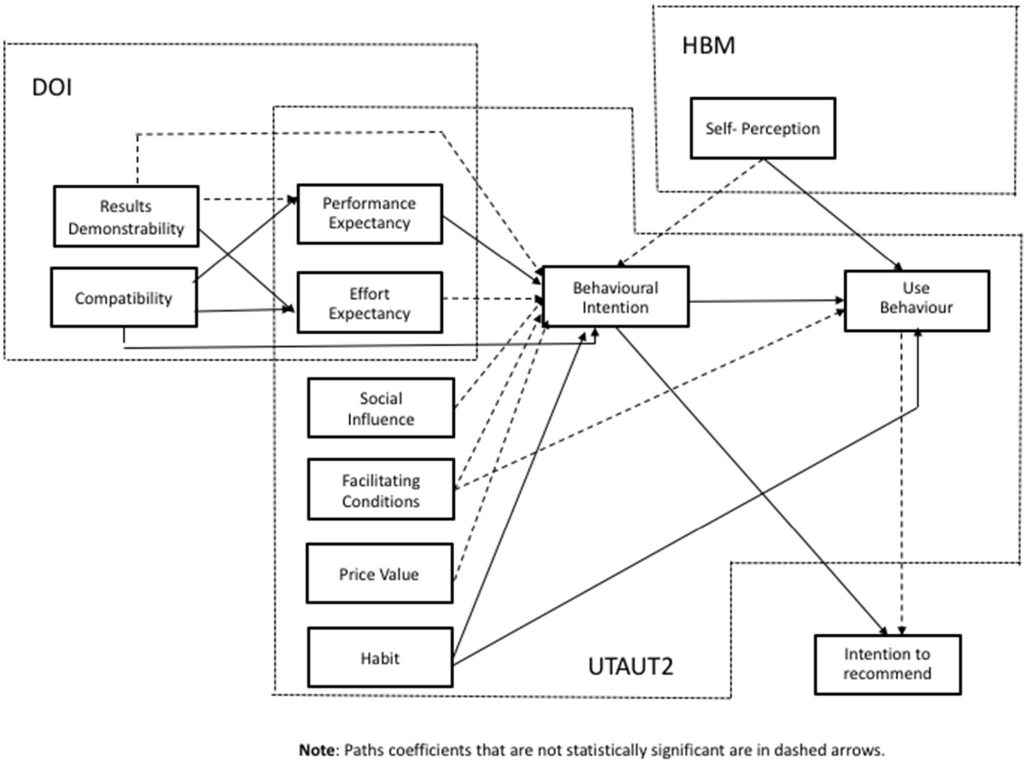


Figure 7.1 Proposed final research model

In the final research model, effort expectancy did not play as strong role as in the previous empirical studies in influencing behavioural intention, still an interaction between effort expectancy, results demonstrability and compatibility exists, making it relevant their inclusion in the model. Within the context of DOI and in other studies of early adopters and new and innovative technologies, for younger and more educated people the complexity of learning a new technology approach seems not to be an issue, with compatibility and performance expectancy being much more valued drivers for adoption and use (Oliveira et al., 2016; Rogers, 2003; Yi et al., 2006). Also as seen in Table 7.1, facilitating conditions seem to have played a minor role in the understanding of the adoption of EHR portals. Still, our early users are younger and more educated than the population average, having the resources (e.g. easy internet access and computer) and knowledge to use the EHR portals. Other studies, mostly qualitative that addressed the reasons and obstacles for older people and from lower socio-economic backgrounds to use EHR portals, found facilitating conditions a significant topic to be addressed (Arauwou, 2017; Nambisan, 2017; Wallace et al., 2016). To keep our model suitable to be used in the future regarding different types of users, facilitating conditions should be retained in the model. Another important contribution of our study was the addition of the intention to recommend construct and to be able to demonstrate its influence in the adoption of EHR portals. Social network marketing and opinions shared by friends and relatives are influential ways to help in the promotion and successful adoption of EHR portals. Overall, we believe that we were able to develop a broad and suitable final research model to study the adoption and use of EHR portals.

7.2 Contributions

This dissertation made several important contributions. Understanding EHR portals adoption factors is, according to the literature, a field of knowledge in which a gap exists. We contributed to fill this gap by studying the reasons why people decide to adopt and use EHR portals. Secondly, we also contributed in this dissertation to provide a clearer definition about this new technology approach, and how it differs from the traditional patient portals and EHR systems. Thirdly we were also able to demonstrate that when studying an IT platform, it is important to contextualize the purpose why it is used and by whom, and that a general single adoption model was not the ideal approach to understand EHR portals adoption complexity. EHR portals are a consumer-centred tool, and a new technology approach in health care. UTAUT2, HBM and DOI are models and theories that are aligned with these assumptions, and all of the models were able to provide significant contributions to our final research model. Fourthly to our best knowledge our line of research is unique, because besides providing a new research model with very good results, we also demonstrated that different countries with different health care approaches can provide different results in specific constructs (e.g. price value in the US vs Portugal). Not only potential cultural differences but also the way a country's healthcare system is managed can influence the way people decide to adopt EHR portals. Also according to our literature review findings, this is a new line of research in this dissertation, that shows that government measures and polices in health care may influence eHealth tools adoption drivers. Fifthly and also to our best knowledge, we provided the first national survey in Portugal that addresses the adoption reasons and usage patterns of EHR portals.

Overall, we hope that by providing the understanding about the factors that lead people to adopt EHR portals, this dissertation helps to design and implement better EHR portals, increasing the current adoption and usage, providing better and more efficient health care services to people, and contributing to the future sustainability of the different worldwide health care systems.

7.3 Managerial Implications

The findings of this dissertation have valuable managerial implications for the conceptualization, design, and implementation of an EHR Portal. According to the findings of our research, when designing or redeploying an EHR Portal it is important to make it simple and easy to use and that the results are easily demonstrable, because perceptions of how easy it is to use a technology are affected by them. Performance expectancy is a consistent driver in all empirical research we conducted. When conceiving and promoting EHR portals it is important to highlight the advantages that they provide to the users in managing their health-related activities more efficiently. We therefore suggest that a pilot application of the platform to be tested by the potential users so that improvements and alignment with the users' needs can be made during the development stage to increase the platform's acceptance. Compatibility is also a relevant construct in our model and it is important to develop EHR portals that fit the health care customer's life style. A good suggestion is to providers of EHR portals to develop mobile versions of their EHR portals, allowing people to access their data everywhere.

Habit also plays a relevant role in our empirical research. Since it is defined as the degree to which individuals tend to execute behaviours automatically because of learning, it is advisable that EHR portals have client support services to help users with the platform. In addition to the automatic and direct effect of habit on usage, habit also operates as a stored intention path to influence behaviour (Venkatesh et al., 2012). This demands more marketing communication effort to strengthen both the stored intention and its link to behaviour (Venkatesh et al., 2012). Another important finding is that the construct that is specific to health care—self-perception—also has a significant impact on the EHR portals adoption. Health care interventions that make the patient more conscious of her/his health condition(s) may also endorse the use of the EHR Portal. Also, the inclusion of educational health materials in the EHR portals may encourage patients to use the platform. Another important contribution of our study is that it demonstrates the importance of social influence and the intention to recommend in the adoption process of EHR portals. Social network marketing, opinions shared by friends and relatives, are influential ways to help in the promotion and successful adoption of EHR portals. Particularly in countries and environments where health care is mainly driven by private institutions and without a strong NHS coverage, the price value of EHR portals is more significantly perceived by the patient. It is important to highlight the savings and value that can be gained by the patient, for example by requesting on-line prescription renewal and appointments, avoiding unnecessary trips to the hospital or clinic.

Although in our research that interviewed users of EHR portals, confidentiality concerns do not seem to be an issue for EHR portals adoption, according to literature, if not exposed to positive argumentation and communication in favour of their use, non-users may be affected by confidentiality concerns (Angst & Agarwal, 2009). It is recommended to provide positive argumentation about EHR portals that reassures any potential confidential concerns. It is important to mention that recent literature about the on-going implementation of meaningful use in US shows that there is a higher trust in health care institutions and less privacy concerns than before, due to the current initiatives already on going sponsored by the federal government to highlight the advantages of sharing with the patients their EHR information (Ancker, Brenner, et al., 2015; Mackert et al., 2016). Also, an interesting fact is that in the last empirical study (Chapter 6), EHR portals usage patterns in Portugal increased versus the previous empirical studies in this dissertation. There is an ongoing offer increase of EHR portals in Portugal by different health care providers, with some of them implementing measures to discourage the patient to use the traditional channels of contact and to receive the exams results in paper format, and to use instead the web portal (CUF, 2017; Tavares et al., in press). We believe that the insights obtained with our research will help policy makers and health care providers to implement and develop better EHR portals in different countries and environments including different types of users.

7.4 Limitations and Future Work

We acknowledge that this dissertation has several limitations. Regarding the first three empirical studies, we used samples from educational institutions. The reasons why we used this approach is that according to the literature, EHR portals are a technology with a low usage prevalence (Gheorghiu & Hagens, 2017), and it is feasible to use a sampling strategy that targets where this population is more concentrated (Kalton & Anderson, 1986; Picot et al., 2001). According to the literature the EHR Portal users are younger and more educated (Ancker, Osorio, et al., 2015; Or & Karsh, 2009; Smith et al., 2015; Zhang et al., 2015), making educational institutions a good place to execute our survey. Nevertheless, due to this sampling methodology we cannot affirm that our sample is representative of the target population, adults with more than 18 years old. Our last empirical study used a random sampling approach targeting the adults with more than 18 years of age, but with a high non-response rate that limits the results' representativeness. When conducting surveys via telephone interviews it is wise to limit the questions to those that are strictly necessary to the study's purpose, to reduce the interview time and encourage people to finish the interview. It is also wise to mention the relevance and importance of the study to the society, to encourage people to answer.

Our last empirical research produced the final research model, which obtained the best results, but was tested in only one country. Previous empirical research demonstrated the usefulness of testing a model in different countries to assess potential differences. It would make sense to test the final research model from Chapter 6 in a country with a different health care system, as we did in Chapter 5. The comparison between countries may also focus on cross-cultural differences (e.g. Europe versus Middle-East), and extend the model to incorporate dimensions and scales that can better address it. In our dissertation, we performed our empirical research with users of EHR portals. It could be useful to refine and adapt our existing model to assess the factors that may lead non-users to become users (e.g. do not focus on use behaviour, instead target behavioural intention, and test confidentiality concerns again). Currently several providers of EHR portals are starting to develop mobile versions (Mackert et al., 2016; O'Leary et al., 2016). We found that one of the most important factors for the adoption of EHR portals is compatibility, meaning that people want to have tools that fit in their current lifestyle. Taking into account the current high usage of mobile devices and health apps, evaluating the usefulness of mobile health within the scope of EHR portals is an interesting avenue of research.

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Appendixes

Appendix 3.1 Questionnaire's items

Electronic health record portals are based on applying information technologies and systems on health environments. These portals allow, for instance, to make medical appointments online, to access medical history, medication records, specialists' summaries, and laboratory results. The access to these services is made through a web page, and allows you, as a patient, to manage your medical records.

Please answer the questionnaire only if you have prior knowledge and contact with electronic health record portals.

When we mention "EHR Portals" in this questionnaire, it refers to electronic health record portals.

Construct	Code	Items	Reference
Performance Expectancy	PE1	Using EHR Portals will support critical aspects of my health care.	(Wilson & Lankton, 2004)
	PE2	Using EHR Portals will enhance my effectiveness in managing my health care.	
	PE3	Overall, EHR Portals will be useful in managing my health care.	
Effort Expectancy	EE1	Learning how to use EHR Portals is easy for me.	(Venkatesh et al., 2012)
	EE2	My interaction with EHR Portals is clear and understandable.	
	EE3	I find EHR Portals easy to use.	
	EE4	It is easy for me to become skilful at using EHR Portals.	
Social Influence	SI1	People who are important to me think that I should use EHR Portals.	(Venkatesh et al., 2012)
	SI2	People who influence my behaviour think that I should use EHR Portals.	
	SI3	People whose opinions that I value prefer that I use EHR Portals.	
Facilitating Conditions	FC1	I have the resources necessary to use EHR Portals.	(Venkatesh et al., 2012)
	FC2	I have the knowledge necessary to use EHR Portals.	
	FC3	EHR Portals is compatible with other technologies I use.	
	FC4	I can get help from others when I have difficulties using EHR Portals.	
Hedonic Motivation	HM1	Using EHR Portals is fun.	(Venkatesh et al., 2012)
	HM2	Using EHR Portals is enjoyable.	
	HM3	Using EHR Portals is very entertaining.	
Price Value	PV1	EHR Portals is reasonably priced.	(Venkatesh et al., 2012)
	PV2	EHR Portals is a good value for the money.	
	PV3	At the current price, EHR Portals provides a good value.	
Habit	HT1	The use of EHR Portals has become a habit for me.	(Venkatesh et al., 2012)
	HT2	I am addicted to using EHR Portals.	
	HT3	I must use EHR Portals.	
Behavioural Intention	BI1	I intend to use EHR Portals.	(Venkatesh et al., 2012)
	BI2	I intend to use EHR Portals in the next months.	
	BI3	I plan to use EHR Portals frequently.	
Technology use	UB1	What is your actual frequency of use of EHR Portals? (i) Never; to (vii) every time I need it.	(Martins et al., 2014)

Appendix 4.1 Questionnaire's items

The scales' items were measured on a seven-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7). Use was measured on a different scale (explained in the table below).

Construct	Code	Items	Reference
Performance Expectancy	PE1	Using EHR Portals will support critical aspects of my healthcare.	(Wilson & Lankton, 2004)
	PE2	Using EHR Portals will enhance my effectiveness in managing my healthcare.	
	PE3	Overall, EHR Portals will be useful in managing my healthcare.	
Effort Expectancy	EE1	Learning how to use EHR Portals is easy for me.	(Venkatesh et al., 2012)
	EE2	My interaction with EHR Portals is clear and understandable.	
	EE3	I find EHR Portals easy to use.	
	EE4	It is easy for me to become skilful at using EHR Portals.	
Social Influence	SI1	People who are important to me think that I should use EHR Portals.	(Venkatesh et al., 2012)
	SI2	People who influence my behaviour think that I should use EHR Portals.	
	SI3	People whose opinions that I value prefer that I use EHR Portals.	
Facilitating Conditions	FC1	I have the resources necessary to use EHR Portals.	(Venkatesh et al., 2012)
	FC2	I have the knowledge necessary to use EHR Portals.	
	FC3	EHR Portals is compatible with other technologies I use.	
	FC4	I can get help from others when I have difficulties using EHR Portals.	
Hedonic Motivation	HM1	Using EHR Portals is fun.	(Venkatesh et al., 2012)
	HM2	Using EHR Portals is enjoyable.	
	HM3	Using EHR Portals is very entertaining.	
Price Value	PV1	EHR Portals is reasonably priced.	(Venkatesh et al., 2012)
	PV2	EHR Portals is a good value for the money.	
	PV3	At the current price, EHR Portals provides a good value.	
Habit	HT1	The use of EHR Portals has become a habit for me.	(Venkatesh et al., 2012)
	HT2	I am addicted to using EHR Portals.	
	HT3	I must use EHR Portals.	
Self-Perception	SP1	Do you think your health complaints are serious?	(Vandekar et al., 1992)
	SP2	Do you think your health complaints have to do with a serious disease?	
	SP4	Do you think that you could have treated your health complaints yourself?	
	SP6	Do you need more information about your health complaints?	
Behavioural Intention	BI1	I intend to use EHR Portals.	(Venkatesh et al., 2012)
	BI2	I intend to use EHR Portals in the next months.	
	BI3	I plan to use EHR Portals frequently.	
Use Behaviour		What is your actual frequency of use of the following EHR Portal services? (i) Never; to (vii) every time I need it.	(Venkatesh et al., 2012)
	UB1	Management of Personal Information and communication with health providers.	
	UB2	Medical appointments schedule.	
	UB3	Check your own Electronic Health Record.	
	UB4	Request for medical prescription renewals.	

(cont. Appendix 4.1)

Introduction presented to respondents before the questionnaire started:

Electronic health record portals are based on applying information technologies and systems on health environments. These portals allow, for instance, to make medical appointments online, to access medical history, medication records, specialists' summaries, and laboratory results. The access to these services is made through a web page, and allows you, as a patient, to manage your medical records. Please answer the questionnaire only if you have prior knowledge and contact with electronic health record portals. When we mention "EHR Portals" in this questionnaire, it refers to electronic health record portals.

Appendix 4.2 PLS loadings and cross-loadings

Construct	Item	BI	EE	FC	HT	SP	HM	PE	PV	SI
Behavioural Intention (BI)	BI1	**0.89**	0.47	0.32	0.58	0.11	0.45	0.54	0.33	0.36
	BI2	**0.94**	0.37	0.24	0.54	0.16	0.38	0.43	0.31	0.40
	BI3	**0.91**	0.32	0.22	0.56	0.21	0.36	0.41	0.33	0.43
Effort Expectancy (EE)	EE1	0.36	**0.87**	0.51	0.19	-0.10	0.32	0.35	0.26	0.15
	EE3	0.40	**0.91**	0.50	0.28	-0.07	0.44	0.47	0.32	0.25
	EE4	0.34	**0.86**	0.49	0.29	-0.08	0.44	0.40	0.33	0.24
	EE5	0.40	**0.91**	0.52	0.27	-0.03	0.37	0.43	0.28	0.20
Facilitating conditions (FC)	FC1	0.20	0.42	**0.80**	0.14	-0.05	0.16	0.17	0.14	0.09
	FC2	0.24	0.49	**0.88**	0.21	-0.03	0.23	0.20	0.23	0.20
	FC3	0.28	0.53	**0.84**	0.19	-0.06	0.27	0.27	0.17	0.15
	FC4	0.18	0.32	**0.64**	0.28	-0.05	0.34	0.13	0.27	0.29
Habit (HT)	H1	0.52	0.23	0.24	**0.88**	0.15	0.33	0.30	0.42	0.59
	H2	0.40	0.13	0.16	**0.81**	0.18	0.39	0.24	0.37	0.44
	H3	0.56	0.34	0.22	**0.75**	0.08	0.46	0.50	0.32	0.31
Self-Perception (SP)	SP1	0.10	-0.11	-0.11	0.06	**0.80**	0.03	0.00	0.04	0.06
	SP2	0.15	-0.09	-0.12	0.11	**0.85**	0.01	0.01	0.03	0.15
	SP4	0.11	-0.05	-0.01	0.13	**0.54**	0.07	-0.02	0.11	0.14
	SP6	0.13	0.01	0.07	0.15	**0.65**	0.14	0.11	0.05	0.07
Hedonic Motivation (HM)	HM1	0.41	0.37	0.27	0.46	0.12	**0.96**	0.43	0.41	0.31
	HM2	0.41	0.50	0.37	0.44	0.01	**0.90**	0.49	0.37	0.28
	HM3	0.41	0.38	0.25	0.45	0.11	**0.96**	0.41	0.40	0.30
Performance Expectancy (PE)	PE1	0.37	0.39	0.18	0.30	0.04	0.39	**0.86**	0.26	0.18
	PE2	0.51	0.45	0.25	0.42	0.05	0.46	**0.95**	0.29	0.29
	PE3	0.48	0.44	0.23	0.45	0.02	0.44	**0.92**	0.32	0.35
Price Value (PV)	PV1	0.30	0.27	0.22	0.37	0.09	0.34	0.22	**0.91**	0.28
	PV2	0.34	0.34	0.27	0.45	0.07	0.43	0.34	**0.96**	0.32
	PV3	0.35	0.33	0.24	0.46	0.07	0.41	0.33	**0.95**	0.34
Social Influence (SI)	SI1	0.41	0.23	0.22	0.54	0.14	0.27	0.31	0.32	**0.97**
	SI2	0.42	0.23	0.22	0.54	0.15	0.31	0.30	0.33	**0.98**
	SI3	0.44	0.24	0.23	0.55	0.14	0.34	0.30	0.34	**0.98**

Appendix 5.1 Questionnaire items

The scales' items were measured on a seven-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7). Use was measured on a different scale (explained in the table below).

Construct	**Code**	**Items**	**Reference**
Performance Expectancy	PE1	Using EHR Portals will support critical aspects of my healthcare.	(Wilson & Lankton, 2004)
	PE2	Using EHR Portals will enhance my effectiveness in managing my healthcare.	
	PE3	Overall, EHR Portals will be useful in managing my healthcare.	
Effort Expectancy	EE1	Learning how to use EHR Portals is easy for me.	(Venkatesh et al., 2012)
	EE2	My interaction with EHR Portals is clear and understandable.	
	EE3	I find EHR Portals easy to use.	
	EE4	It is easy for me to become skilful at using EHR Portals.	
Social Influence	SI1	People who are important to me think that I should use EHR Portals.	(Venkatesh et al., 2012)
	SI2	People who influence my behaviour think that I should use EHR Portals.	
	SI3	People whose opinions that I value prefer that I use EHR Portals.	
Facilitating Conditions	FC1	I have the resources necessary to use EHR Portals.	(Venkatesh et al., 2012)
	FC2	I have the knowledge necessary to use EHR Portals.	
	FC3	EHR Portals are compatible with other technologies I use.	
	FC4	I can get help from others when I have difficulties using EHR Portals.	
Hedonic Motivation	HM1	Using EHR Portals is fun.	(Venkatesh et al., 2012)
	HM2	Using EHR Portals is enjoyable.	
	HM3	Using EHR Portals is very entertaining.	
Price Value	PV1	EHR Portals is reasonably priced.	(Venkatesh et al., 2012)
	PV2	EHR Portals is a good value for the money.	
	PV3	At the current price, EHR Portals provides a good value.	
Habit	HT1	The use of EHR Portals has become a habit for me.	(Venkatesh et al., 2012)
	HT2	I am addicted to using EHR Portals.	
	HT3	I must use EHR Portals.	
Collection	CL1	It usually bothers me when healthcare entities ask me for personal information.	(Angst & Agarwal, 2009)
	CL2	When healthcare entities ask me for personal information, I sometimes think twice before providing it.	
	CL3	It bothers me to give personal information to so many healthcare entities.	
	CL4	I'm concerned that healthcare entities are collecting too much personal information about me.	

Construct	Code	Items	Reference
Errors	ER1	All the personal information in computer databases should be double-checked for accuracy—no matter how much this costs. (dropped)	(Angst & Agarwal, 2009)
	ER2	Healthcare entities should take more steps to make sure that the personal information in their files is accurate.	
	ER3	Healthcare entities should have better procedures to correct errors in personal information.	
	ER4	Healthcare entities should devote more time and effort to verifying the accuracy of the personal information in their databases.	
Secondary Use	SU1	Healthcare entities should not use personal information for any purpose unless it has been authorized by the individuals who provided the information.	(Angst & Agarwal, 2009)
	SU2	When people give personal information to a company for some reason, the company should never use the information for any other reason.	
	SU3	Healthcare entities should never sell the personal information in their computer databases to other healthcare entities.	
	SU4	Healthcare entities should never share personal information with other healthcare entities unless it has been authorized by the patient who provided the information	
Unauthorized Access	UA1	Healthcare entities should devote more time and effort to preventing unauthorized access to personal information.	(Angst & Agarwal, 2009)
	UA2	Computer databases that contain personal information should be protected from unauthorized access no matter how much it costs.	
	UA3	Healthcare entities should take more steps to make sure that unauthorized people cannot access personal information in their computers.	
Behavioural Intention	BI1	I intend to use EHR Portals.	(Venkatesh et al., 2012)
	BI2	I intend to use EHR Portals in the next months.	
	BI3	I plan to use EHR Portals frequently.	
Use Behaviour		What is your actual frequency of use of the following EHR Portal services? (1) Never; to (7) every time I need it.	(Venkatesh et al., 2012)
	UB1	Management of Personal Information and communication with health providers.	
	UB2	Medical appointments schedule.	
	UB3	Check your own Electronic Health Record.	
	UB4	Check your medical exams results (dropped)	
	UB5	Request for medical prescription renewals.	

(cont. Appendix 5.1)

Introduction about EHR Portals presented to respondents before administering the questionnaire:

Electronic health record portals are based on applying information technologies and systems on health environments. These portals allow, for instance, to make medical appointments online, to access medical history, medication records, specialists' summaries, and laboratory results. The access to these services is made through a web page, and allows you, as a patient, to manage your medical records. Please answer the questionnaire only if you have prior knowledge and contact with electronic health record portals. When we mention "EHR Portals" in this questionnaire, it refers to electronic health record portals.

Appendix 5.2 PLS loadings and cross-loadings

Table 5.2A1 PLS loadings and cross-loadings total model

Construct	Item	BI	CL	ER	SU	UA	EE	FC	HT	HM	PE	PV	SI
Behavioural intention (BI)	BI1	**0.91**	-0.10	0.12	0.15	0.17	0.50	0.44	0.50	0.32	0.60	0.44	0.43
	BI2	**0.93**	-0.01	0.01	0.05	0.08	0.40	0.34	0.52	0.25	0.50	0.45	0.47
	BI3	**0.92**	-0.05	-0.01	0.04	0.04	0.36	0.34	0.46	0.18	0.48	0.47	0.50
Collection (CL)	CL1	-0.10	**0.71**	-0.04	-0.04	0.01	-0.16	-0.14	0.10	-0.04	-0.12	-0.11	0.03
	CL2	-0.07	**0.87**	-0.04	-0.06	-0.01	-0.16	-0.13	0.08	-0.02	-0.11	-0.04	0.06
	CL3	-0.07	**0.86**	0.04	0.03	0.07	-0.13	-0.08	0.04	-0.05	-0.06	-0.06	0.03
	CL4	-0.07	**0.97**	-0.01	-0.03	0.03	-0.18	-0.12	0.08	-0.05	-0.09	-0.05	0.07
Errors (ER)	ER2	0.08	0.00	**0.93**	0.51	0.68	0.24	0.29	-0.07	0.09	0.25	0.13	-0.07
	ER3	0.03	-0.01	**0.99**	0.49	0.66	0.21	0.24	-0.11	0.07	0.23	0.07	-0.12
	ER4	0.03	0.08	**0.85**	0.43	0.60	0.17	0.21	-0.03	0.10	0.21	0.10	-0.06
Secondary use (SU)	SU1	0.09	-0.03	0.48	**0.91**	0.61	0.27	0.36	-0.14	0.03	0.22	0.10	-0.11
	SU2	0.07	-0.01	0.46	**0.90**	0.58	0.27	0.32	-0.09	0.04	0.18	0.10	-0.10
	SU3	0.07	0.01	0.42	**0.75**	0.52	0.22	0.30	-0.17	0.02	0.19	0.08	-0.08
	SU4	0.08	-0.05	0.39	**0.79**	0.50	0.19	0.29	-0.14	0.01	0.17	0.09	-0.03
Unauthorized access (UA)	UA1	0.11	0.05	0.65	0.61	**0.95**	0.30	0.36	-0.09	0.06	0.24	0.11	-0.13
	UA2	0.14	0.02	0.61	0.60	**0.82**	0.29	0.35	-0.07	0.05	0.25	0.16	-0.09
	UA3	0.09	0.01	0.67	0.63	**0.96**	0.30	0.37	-0.10	0.06	0.23	0.12	-0.15
Effort expectancy (EE)	EE1	0.37	-0.17	0.24	0.27	0.33	**0.90**	0.63	0.17	0.32	0.40	0.30	0.08
	EE2	0.44	-0.15	0.17	0.22	0.24	**0.93**	0.60	0.28	0.38	0.48	0.39	0.24
	EE3	0.41	-0.14	0.17	0.24	0.26	**0.90**	0.61	0.27	0.36	0.46	0.38	0.22
	EE4	0.42	-0.16	0.26	0.30	0.32	**0.92**	0.64	0.23	0.34	0.47	0.35	0.16
Facilitating conditions (FC)	FC1	0.30	-0.12	0.25	0.37	0.36	0.55	**0.82**	0.13	0.15	0.33	0.25	0.07
	FC2	0.37	-0.08	0.26	0.35	0.38	0.62	**0.90**	0.20	0.21	0.38	0.33	0.17
	FC3	0.37	-0.12	0.25	0.30	0.32	0.62	**0.84**	0.15	0.22	0.40	0.25	0.12
	FC4	0.25	-0.04	0.06	0.14	0.15	0.37	**0.64**	0.25	0.30	0.23	0.29	0.31
Habit (HT)	HT1	0.59	0.03	-0.09	-0.08	-0.06	0.29	0.28	**0.93**	0.34	0.40	0.47	0.59
	HT2	0.26	0.13	-0.16	-0.23	-0.22	0.05	0.03	**0.78**	0.44	0.15	0.26	0.42
	HT3	0.27	0.04	0.07	-0.02	0.02	0.23	0.13	**0.62**	0.50	0.31	0.21	0.21
Hedonic motivation (HM)	HM1	0.28	-0.04	0.05	0.02	0.06	0.34	0.25	0.45	**0.95**	0.38	0.34	0.28
	HM2	0.27	-0.05	0.11	0.07	0.10	0.43	0.31	0.43	**0.93**	0.41	0.31	0.25
	HM3	0.21	-0.03	0.06	0.00	0.02	0.30	0.19	0.43	**0.94**	0.30	0.27	0.24
Performance expectancy (PE)	PE1	0.41	-0.10	0.27	0.22	0.27	0.43	0.36	0.30	0.38	**0.87**	0.31	0.24
	PE2	0.56	-0.06	0.23	0.21	0.23	0.48	0.42	0.35	0.36	**0.95**	0.39	0.34
	PE3	0.57	-0.06	0.19	0.18	0.19	0.46	0.39	0.39	0.34	**0.94**	0.42	0.40
Price value (PV)	PV1	0.43	0.02	0.10	0.13	0.13	0.34	0.32	0.38	0.26	0.32	**0.92**	0.30
	PV2	0.48	-0.04	0.09	0.12	0.12	0.39	0.35	0.43	0.34	0.43	**0.96**	0.36
	PV3	0.49	-0.05	0.08	0.07	0.10	0.38	0.33	0.44	0.33	0.41	**0.96**	0.38
Social influence (SI)	SI1	0.49	0.07	-0.10	-0.09	-0.13	0.19	0.20	0.56	0.25	0.36	0.37	**0.97**
	SI2	0.49	0.08	-0.11	-0.10	-0.14	0.20	0.20	0.55	0.28	0.34	0.35	**0.98**
	SI3	0.50	0.07	-0.12	-0.10	-0.14	0.18	0.20	0.57	0.28	0.36	0.36	**0.98**

Table 5.2A2 PLS loadings and cross-loadings US model

Construct	Item	BI	CL	ER	SU	UA	EE	FC	HT	HM	PE	PV	SI
Behavioural intention (BI)	BI1	**0.96**	-0.16	0.22	0.31	0.33	0.60	0.62	0.44	0.28	0.67	0.54	0.43
	BI2	**0.92**	-0.14	0.13	0.22	0.24	0.51	0.53	0.51	0.27	0.58	0.56	0.45
	BI3	**0.95**	-0.23	0.29	0.36	0.37	0.61	0.63	0.36	0.27	0.66	0.55	0.40
Collection (CL)	CL1	-0.20	**0.92**	-0.13	-0.16	-0.09	-0.17	-0.20	0.08	-0.05	-0.28	-0.16	-0.02
	CL2	-0.20	**0.93**	-0.11	-0.16	-0.10	-0.21	-0.24	0.00	-0.06	-0.26	-0.13	-0.02
	CL3	-0.13	**0.94**	0.00	-0.02	0.04	-0.11	-0.12	-0.04	-0.09	-0.17	-0.12	-0.06
	CL4	-0.19	**0.91**	-0.03	-0.12	0.00	-0.19	-0.20	-0.01	-0.09	-0.25	-0.17	-0.04
Errors (ER)	ER2	0.25	-0.07	**0.92**	0.57	0.64	0.25	0.36	-0.06	-0.01	0.33	0.28	0.06
	ER3	0.21	-0.09	**0.91**	0.52	0.60	0.21	0.31	-0.12	-0.05	0.28	0.22	0.00
	ER4	0.18	-0.04	**0.93**	0.43	0.55	0.18	0.25	-0.01	0.01	0.25	0.24	0.04
Secondary use (SU)	SU1	0.32	-0.16	0.50	**0.91**	0.72	0.35	0.50	-0.13	-0.10	0.34	0.29	-0.03
	SU2	0.28	-0.08	0.51	**0.88**	0.68	0.31	0.40	-0.08	-0.07	0.28	0.25	-0.05
	SU3	0.27	-0.10	0.46	**0.86**	0.61	0.31	0.45	-0.18	-0.04	0.31	0.29	-0.02
	SU4	0.24	-0.10	0.44	**0.87**	0.66	0.30	0.45	-0.17	-0.06	0.29	0.26	-0.04
Unauthorized access (UA)	UA1	0.32	0.00	0.58	0.65	**0.90**	0.32	0.44	-0.11	-0.07	0.32	0.25	-0.07
	UA2	0.31	-0.07	0.54	0.72	**0.90**	0.35	0.48	-0.09	-0.10	0.32	0.34	-0.03
	UA3	0.27	-0.03	0.64	0.71	**0.91**	0.33	0.47	-0.11	-0.09	0.30	0.28	-0.09
Effort expectancy (EE)	EE1	0.56	-0.16	0.22	0.35	0.37	**0.94**	0.74	0.24	0.26	0.48	0.43	0.17
	EE2	0.56	-0.15	0.17	0.28	0.30	**0.93**	0.71	0.32	0.33	0.51	0.46	0.26
	EE3	0.57	-0.17	0.20	0.33	0.31	**0.93**	0.74	0.28	0.29	0.53	0.43	0.25
	EE4	0.58	-0.18	0.26	0.39	0.39	**0.94**	0.78	0.25	0.28	0.53	0.48	0.22
Facilitating conditions (FC)	FC1	0.54	-0.18	0.30	0.49	0.48	0.67	**0.86**	0.12	0.11	0.50	0.43	0.13
	FC2	0.58	-0.17	0.30	0.49	0.48	0.74	**0.90**	0.20	0.16	0.57	0.47	0.20
	FC3	0.59	-0.16	0.33	0.44	0.44	0.71	**0.89**	0.13	0.12	0.56	0.39	0.17
	FC4	0.36	-0.15	0.12	0.22	0.25	0.49	**0.66**	0.20	0.25	0.41	0.29	0.34
Habit (HT)	HT1	0.58	-0.07	0.00	-0.02	0.03	0.40	0.34	**0.93**	0.49	0.48	0.47	0.50
	HT2	0.08	0.15	-0.17	-0.35	-0.33	-0.02	-0.14	**0.72**	0.51	0.05	0.12	0.43
	HT3	0.23	0.07	-0.12	-0.23	-0.22	0.10	-0.02	**0.84**	0.46	0.16	0.25	0.45
Hedonic motivation (HM)	HM1	0.27	-0.07	-0.02	-0.06	-0.06	0.29	0.18	0.51	**0.95**	0.34	0.32	0.44
	HM2	0.32	-0.10	0.00	-0.05	-0.08	0.34	0.22	0.55	**0.96**	0.38	0.37	0.47
	HM3	0.17	-0.01	-0.04	-0.15	-0.17	0.20	0.06	0.50	**0.90**	0.21	0.22	0.42
Performance expectancy (PE)	PE1	0.61	-0.26	0.27	0.29	0.28	0.47	0.52	0.39	0.33	**0.93**	0.44	0.43
	PE2	0.65	-0.23	0.31	0.33	0.33	0.54	0.62	0.33	0.30	**0.95**	0.49	0.39
	PE3	0.66	-0.23	0.30	0.34	0.36	0.54	0.61	0.34	0.34	**0.96**	0.50	0.41
Price value (PV)	PV1	0.50	-0.08	0.28	0.33	0.32	0.44	0.45	0.36	0.25	0.42	**0.93**	0.22
	PV2	0.59	-0.19	0.24	0.29	0.31	0.47	0.47	0.41	0.35	0.51	**0.96**	0.32
	PV3	0.57	-0.17	0.25	0.26	0.30	0.46	0.46	0.39	0.36	0.50	**0.96**	0.32
Social influence (SI)	SI1	0.44	-0.04	0.04	-0.04	-0.05	0.24	0.24	0.52	0.47	0.42	0.32	**0.96**
	SI2	0.42	-0.03	0.02	-0.04	-0.08	0.25	0.23	0.52	0.46	0.39	0.27	**0.96**
	SI3	0.44	-0.03	0.04	-0.03	-0.07	0.21	0.22	0.54	0.45	0.43	0.28	**0.97**

Table 5.2A3 PLS loadings and cross-loadings Portugal model

Construct	Item	BI	CL	ER	SU	UA	EE	FC	HT	HM	PE	PV	SI
Behavioural intention (BI)	BI1	**0.89**	-0.06	0.11	0.04	-0.15	0.47	0.33	0.59	0.46	0.53	0.33	0.39
	BI2	**0.93**	0.05	0.06	-0.01	-0.11	0.36	0.24	0.55	0.38	0.43	0.32	0.40
	BI3	**0.90**	0.03	-0.03	-0.09	-0.03	0.31	0.24	0.58	0.36	0.40	0.35	0.42
Collection (CL)	CL1	0.02	**0.91**	-0.04	0.07	-0.06	-0.18	-0.10	0.12	-0.05	0.02	-0.05	0.12
	CL2	0.02	**0.95**	-0.02	0.04	-0.09	-0.12	-0.05	0.15	0.00	0.02	0.03	0.13
	CL3	-0.03	**0.94**	0.02	0.09	-0.07	-0.16	-0.06	0.11	-0.03	0.04	-0.01	0.11
	CL4	0.00	**0.92**	-0.04	0.07	-0.08	-0.17	-0.05	0.14	0.00	0.05	0.03	0.15
Errors (ER)	ER2	0.06	0.05	**0.92**	0.42	-0.70	0.20	0.20	0.01	0.10	0.21	0.08	-0.04
	ER3	0.05	0.04	**0.92**	0.43	-0.68	0.18	0.16	-0.01	0.08	0.22	0.05	-0.05
	ER4	0.04	0.14	**0.59**	0.39	-0.62	0.13	0.16	0.03	0.10	0.20	0.07	0.00
Secondary use (SU)	SU1	-0.02	0.07	0.40	**0.84**	-0.52	0.15	0.22	-0.08	0.11	0.14	-0.01	-0.09
	SU2	-0.02	0.06	0.34	**0.89**	-0.45	0.20	0.22	-0.04	0.09	0.11	0.02	-0.05
	SU3	-0.04	0.12	0.34	**0.88**	-0.46	0.12	0.17	-0.12	0.05	0.09	-0.07	-0.10
	SU4	0.00	0.03	0.26	**0.82**	-0.39	0.08	0.16	-0.09	0.04	0.09	-0.02	0.00
Unauthorized access (UA)	UA1	0.09	0.09	0.62	0.52	**-0.91**	0.24	0.26	0.02	0.10	0.20	0.08	-0.01
	UA2	0.12	0.10	0.55	0.44	**-0.94**	0.18	0.21	0.02	0.12	0.22	0.07	-0.01
	UA3	0.10	0.05	0.62	0.52	**-0.98**	0.22	0.26	-0.01	0.13	0.21	0.08	-0.03
Effort expectancy (EE)	EE1	0.36	-0.19	0.16	0.13	-0.21	**0.87**	0.52	0.19	0.33	0.35	0.27	0.15
	EE2	0.40	-0.15	0.18	0.15	-0.18	**0.91**	0.49	0.28	0.46	0.47	0.34	0.27
	EE3	0.33	-0.11	0.15	0.13	-0.19	**0.86**	0.49	0.29	0.46	0.39	0.36	0.24
	EE4	0.40	-0.14	0.22	0.17	-0.22	**0.91**	0.51	0.27	0.38	0.43	0.29	0.21
Facilitating conditions (FC)	FC1	0.20	-0.07	0.14	0.22	-0.22	0.41	**0.79**	0.17	0.17	0.17	0.14	0.11
	FC2	0.27	-0.02	0.19	0.23	-0.29	0.49	**0.90**	0.23	0.24	0.24	0.25	0.20
	FC3	0.28	-0.12	0.13	0.17	-0.17	0.53	**0.82**	0.20	0.29	0.28	0.18	0.17
	FC4	0.17	0.01	0.05	0.11	-0.10	0.31	**0.61**	0.29	0.36	0.12	0.29	0.31
Habit (HT)	HT1	0.54	0.12	-0.07	-0.10	0.02	0.23	0.26	**0.88**	0.34	0.32	0.43	0.61
	HT2	0.41	0.14	-0.12	-0.14	0.06	0.13	0.18	**0.81**	0.41	0.26	0.37	0.44
	HT3	0.57	0.08	0.12	0.02	-0.09	0.33	0.23	**0.76**	0.48	0.50	0.34	0.32
Hedonic motivation (HM)	HM1	0.41	-0.03	0.03	0.05	-0.11	0.38	0.29	0.48	**0.95**	0.43	0.43	0.31
	HM2	0.42	-0.01	0.11	0.12	-0.15	0.51	0.39	0.45	**0.90**	0.50	0.38	0.29
	HM3	0.41	-0.02	0.05	0.06	-0.09	0.39	0.27	0.47	**0.95**	0.41	0.42	0.30
Performance expectancy (PE)	PE1	0.37	0.02	0.22	0.12	-0.23	0.39	0.20	0.31	0.40	**0.86**	0.27	0.22
	PE2	0.50	0.06	0.16	0.13	-0.22	0.44	0.26	0.42	0.46	**0.95**	0.30	0.30
	PE3	0.48	0.01	0.16	0.09	-0.17	0.44	0.25	0.46	0.43	**0.92**	0.33	0.35
Price value (PV)	PV1	0.32	0.03	0.05	0.00	-0.10	0.29	0.23	0.39	0.37	0.23	**0.91**	0.29
	PV2	0.34	0.00	0.05	0.00	-0.06	0.36	0.28	0.46	0.44	0.35	**0.96**	0.32
	PV3	0.37	-0.02	0.05	-0.04	-0.06	0.35	0.26	0.47	0.42	0.34	**0.95**	0.35
Social influence (SI)	SI1	0.42	0.13	-0.06	-0.04	0.01	0.24	0.24	0.55	0.27	0.32	0.32	**0.97**
	SI2	0.43	0.15	-0.07	-0.06	0.01	0.24	0.24	0.55	0.31	0.31	0.33	**0.98**
	SI3	0.44	0.13	-0.08	-0.07	0.03	0.24	0.25	0.56	0.34	0.32	0.34	**0.98**

Appendix 6.1 Questionnaire's items

The scales' items were measured on a seven-point Likert scale, ranging from "strongly disagree" (1) to "strongly agree" (7). Use was measured on a different scale (explained in the table below).

Construct	**Code**	**Items**	**Reference**
Performance Expectancy	PE1	Using EHR Portals will support critical aspects of my healthcare.	(Wilson & Lankton, 2004)
	PE2	Using EHR Portals will enhance my effectiveness in managing my healthcare.	
	PE3	Overall, EHR Portals will be useful in managing my healthcare.	
Effort Expectancy	EE1	Learning how to use EHR Portals is easy for me.	(Venkatesh et al., 2012)
	EE2	My interaction with EHR Portals is clear and understandable.	
	EE3	I find EHR Portals easy to use.	
	EE4	It is easy for me to become skilful at using EHR Portals.	
Social Influence	SI1	People who are important to me think that I should use EHR Portals.	(Venkatesh et al., 2012)
	SI2	People who influence my behaviour think that I should use EHR Portals.	
	SI3	People whose opinions that I value prefer that I use EHR Portals.	
Facilitating Conditions	FC1	I have the resources necessary to use EHR Portals.	(Venkatesh et al., 2012)
	FC2	I have the knowledge necessary to use EHR Portals.	
	FC3	EHR Portals is compatible with other technologies I use.	
	FC4	I can get help from others when I have difficulties using EHR Portals.	
Hedonic Motivation	HM1	Using EHR Portals is fun.	(Venkatesh et al., 2012)
	HM2	Using EHR Portals is enjoyable.	
	HM3	Using EHR Portals is very entertaining.	
Price Value	PV1	EHR Portals is reasonably priced.	(Venkatesh et al., 2012)
	PV2	EHR Portals is a good value for the money.	
	PV3	At the current price, EHR Portals provides a good value.	
Habit	HT1	The use of EHR Portals has become a habit for me.	(Venkatesh et al., 2012)
	HT2	I am addicted to using EHR Portals.	
	HT3	I must use EHR Portals.	
Self-Perception	SP1	Do you think your health complaints are serious?	(Vandekar et al., 1992)
	SP2	Do you think your health complaints have to do with a serious disease?	
	SP3	Do you need more information about your health complaints	
	SP4	Do you think that you could have treated your health complaints yourself? (dropped)	
Results Demonstrability	RD1	I would have no difficulty telling others about the results of using a EHR Portal	(Moore & Benbasat, 1991)
	RD2	I believe I could communicate to others the consequence of using a EHR Portal	
	RD3	The results of using a EHR are apparent to me	
Compatibility	CO1	Using a EHR Portal is compatible with all aspects of managing my health	(Moore & Benbasat, 1991)
	CO2	Using a EHR Portal is compatible with my current situation	
	CO3	I think that using a EHR Portal fits well with the way I like to manage my health	
	CO4	Using a EHR Portal fits in my life style	

Construct	Code	Items	Reference
Behavioural Intention to recommend	IR1 IR2	I will recommend to my friends to use EHR Portals service, if it is available If I have a good experience with EHR Portals I will recommend friends to use the service	(Oliveira et al., 2016)
Behavioural Intention	BI1 BI2 BI3	I intend to use EHR Portals. I intend to use EHR Portals in the next months. I plan to use EHR Portals frequently.	(Venkatesh et al., 2012)
Use Behaviour	 UB1 UB2 UB3 UB4	What is your actual frequency of use of the following EHR Portal services? (i) Never; to (vii) every time I need it. Management of Personal Information and communication with health providers. Medical appointments schedule. Check your own Electronic Health Record. Request for medical prescription renewals.	(Venkatesh et al., 2012)

Note: It was also asked what was the actual EHR Portal global frequency of use. (i) Never; to (vii) every time I need it.

Appendix 6.2

Table 6.2A1 Cross- Loadings

Construct	Item	BI	CO	EE	FC	HT	IR	PE	PV	RD	SI	SP
Behavioural intention (BI)	BI1	**0.93**	0.72	0.50	0.56	0.62	0.75	0.65	0.47	0.55	0.43	0.45
	BI2	**0.93**	0.72	0.53	0.51	0.70	0.76	0.66	0.54	0.58	0.51	0.58
	BI3	**0.95**	0.82	0.55	0.64	0.65	0.81	0.64	0.55	0.60	0.43	0.42
Compatibility (CO)	CO1	0.66	**0.93**	0.61	0.58	0.54	0.69	0.52	0.53	0.72	0.38	0.38
	CO2	0.72	**0.95**	0.63	0.61	0.58	0.72	0.56	0.52	0.71	0.39	0.40
	CO3	0.80	**0.95**	0.59	0.59	0.61	0.78	0.69	0.56	0.74	0.40	0.46
	CO4	0.78	**0.84**	0.54	0.58	0.52	0.66	0.61	0.51	0.63	0.36	0.35
Effort expectancy (EE)	EE1	0.51	0.59	**0.92**	0.69	0.42	0.53	0.42	0.36	0.61	0.28	0.14
	EE2	0.52	0.59	**0.93**	0.61	0.55	0.58	0.48	0.53	0.60	0.42	0.21
	EE3	0.44	0.50	**0.79**	0.42	0.54	0.47	0.43	0.57	0.49	0.49	0.24
	EE4	0.50	0.57	**0.85**	0.62	0.40	0.56	0.36	0.36	0.60	0.29	0.20
Facilitating conditions (FC)	FC1	0.55	0.55	0.42	**0.78**	0.32	0.45	0.41	0.20	0.37	0.20	0.28
	FC2	0.46	0.50	0.70	**0.83**	0.50	0.44	0.25	0.40	0.48	0.21	0.13
	FC3	0.55	0.63	0.61	**0.90**	0.48	0.59	0.51	0.38	0.58	0.29	0.40
	FC4	0.40	0.40	0.44	**0.72**	0.43	0.43	0.32	0.33	0.44	0.35	0.26
Habit (HT)	HT1	0.60	0.55	0.46	0.49	**0.93**	0.47	0.46	0.62	0.46	0.49	0.50
	HT2	0.57	0.46	0.44	0.43	**0.92**	0.43	0.44	0.57	0.44	0.54	0.57
	HT3	0.72	0.65	0.55	0.51	**0.84**	0.68	0.55	0.64	0.59	0.51	0.41
Intention to Recommend (IR)	IR1	0.85	0.76	0.57	0.56	0.66	**0.96**	0.65	0.55	0.61	0.53	0.45
	IR2	0.70	0.70	0.59	0.56	0.42	**0.93**	0.57	0.45	0.59	0.38	0.29
Performance expectancy (PE)	PE1	0.61	0.57	0.41	0.40	0.46	0.58	**0.88**	0.32	0.51	0.42	0.50
	PE2	0.62	0.62	0.42	0.41	0.46	0.60	**0.93**	0.42	0.47	0.47	0.40
	PE3	0.62	0.54	0.45	0.44	0.52	0.55	**0.85**	0.49	0.43	0.42	0.42
Price value (PV)	PV1	0.52	0.53	0.48	0.39	0.63	0.49	0.39	**0.93**	0.49	0.33	0.17
	PV2	0.54	0.59	0.49	0.38	0.63	0.53	0.46	**0.97**	0.52	0.42	0.24
	PV3	0.53	0.55	0.49	0.39	0.70	0.53	0.48	**0.96**	0.48	0.42	0.29
Results Demonstrability (RD)	RD1	0.51	0.63	0.52	0.49	0.47	0.51	0.46	0.35	**0.88**	0.32	0.44
	RD2	0.53	0.67	0.56	0.53	0.48	0.60	0.47	0.42	**0.95**	0.29	0.46
	RD3	0.61	0.74	0.68	0.53	0.54	0.59	0.49	0.60	**0.87**	0.39	0.32
Social influence (SI)	SI1	0.50	0.42	0.37	0.30	0.54	0.48	0.48	0.38	0.37	**0.96**	0.36
	SI2	0.46	0.38	0.42	0.32	0.54	0.47	0.47	0.36	0.35	**0.98**	0.38
	SI3	0.45	0.40	0.41	0.30	0.58	0.46	0.47	0.44	0.37	**0.95**	0.36
Self - perception (SP)	SP1	0.47	0.37	0.16	0.27	0.51	0.33	0.45	0.23	0.30	0.31	**0.93**
	SP2	0.43	0.40	0.25	0.35	0.52	0.39	0.44	0.21	0.41	0.42	**0.92**
	SP6	0.44	0.35	0.18	0.23	0.38	0.32	0.39	0.19	0.48	0.25	**0,71**

Table 6.2A2- Confidence Intervals for HTMT. Average HTMT values computed from 5000 bootstrap samples (column Sample Mean (M))

[b]	Original Sample (O)	Sample Mean (M)	Bias	2.5%[a]	97.5%[a]
CO -> BI	0.863	0.862	-0.002	0.776	0.920
EE -> BI	0.613	0.615	0.002	0.416	0.756
EE -> CO	0.703	0.702	-0.001	0.498	0.838
FC -> BI	0.691	0.690	-0.001	0.550	0.800
FC -> CO	0.729	0.726	-0.002	0.585	0.837
FC -> EE	0.775	0.770	-0.004	0.611	0.897
HT -> BI	0.779	0.778	-0.000	0.639	0.867
HT -> CO	0.679	0.676	-0.003	0.526	0.790
HT -> EE	0.616	0.613	-0.003	0.449	0.746
HT -> FC	0.629	0.627	-0.002	0.458	0.764
IR -> BI	0.906	0.908	0.003	0.838	0.965
IR -> CO	0.854	0.854	-0.001	0.775	0.916
IR -> EE	0.688	0.684	-0.004	0.520	0.816
IR -> FC	0.695	0.690	-0.005	0.533	0.821
IR -> HT	0.653	0.651	-0.002	0.478	0.771
PE -> BI	0.777	0.776	-0.002	0.647	0.877
PE -> CO	0.720	0.718	-0.002	0.568	0.834
PE -> EE	0.550	0.554	0.004	0.292	0.771
PE -> FC	0.552	0.552	0.000	0.336	0.741
PE -> HT	0.619	0.615	-0.004	0.426	0.771
PE -> IR	0.740	0.743	0.003	0.504	0.888
PV -> BI	0.588	0.586	-0.001	0.469	0.690
PV -> CO	0.614	0.612	-0.002	0.495	0.712
PV -> EE	0.559	0.556	-0.003	0.383	0.706
PV -> FC	0.460	0.458	-0.002	0.277	0.636
PV -> HT	0.747	0.746	-0.001	0.628	0.845
PV -> IR	0.582	0.581	-0.001	0.461	0.693
PV -> PE	0.510	0.508	-0.002	0.340	0.654
RD -> BI	0.674	0.674	0.000	0.540	0.791
RD -> CO	0.835	0.834	-0.001	0.713	0.925
RD -> EE	0.733	0.726	-0.007	0.581	0.846
RD -> FC	0.678	0.673	-0.004	0.502	0.812
RD -> HT	0.629	0.628	-0.001	0.475	0.751
RD -> IR	0.718	0.714	-0.004	0.564	0.840
RD -> PE	0.604	0.605	0.000	0.372	0.773
RD -> PV	0.558	0.556	-0.002	0.415	0.669
SI -> BI	0.515	0.514	-0.001	0.351	0.648
SI -> CO	0.437	0.435	-0.002	0.261	0.597
SI -> EE	0.456	0.453	-0.003	0.268	0.618
SI -> FC	0.366	0.364	-0.002	0.193	0.534
SI -> HT	0.628	0.627	-0.001	0.480	0.745
SI -> IR	0.525	0.525	-0.001	0.358	0.663
SI -> PE	0.542	0.542	0.000	0.366	0.681
SI -> PV	0.428	0.426	-0.002	0.233	0.595
SI -> RD	0.403	0.400	-0.003	0.225	0.556
SP -> BI	0.596	0.599	0.002	0.454	0.724
SP -> CO	0.496	0.498	0.002	0.326	0.638
SP -> EE	0.266	0.276	0.010	0.102	0.467
SP -> FC	0.402	0.410	0.008	0.242	0.578
SP -> HT	0.650	0.652	0.002	0.498	0.776
SP -> IR	0.467	0.470	0.003	0.306	0.608
SP -> PE	0.593	0.595	0.002	0.415	0.747
SP -> PV	0.276	0.281	0.004	0.096	0.462
SP -> RD	0.552	0.553	0.001	0.416	0.676
SP -> SI	0.427	0.430	0.003	0.257	0.583

Notes:

1. [a] Neither of the confidence intervals includes the value of 1;
2. [b] BI: Behavioural intention; CO: Compatibility; EE: Effort expectancy; FC: Facilitating conditions; HT: Habit; IR: Intention to recommend; PE: Performance expectancy; PV: Price value; RD: Results demonstrability; SI: Social influence; SP: Self-Perception;