Impact of Medical History on Technology Adoption in Utah Population Database

Priyanka Chaurasia[1(✉)], Sally I. McClean[2], Chris D. Nugent[1], Ian Cleland[1], Shuai Zhang[1], Mark P. Donnelly[1], Bryan W. Scotney[2], Chelsea Sanders[3], Ken Smith[4], Maria C. Norton[3], and JoAnn Tschanz[3]

[1] School of Computing and Mathematics, University of Ulster, Newtownabbey, Co. Antrim BT37 0QB, Northern Ireland
{p.chaurasia,cd.nugent,i.cleland,s.zhang, mp.donnelly}@ulster.ac.uk

[2] School of Computing and Information Engineering, University of Ulster, Coleraine BT52 1SA, Northern Ireland
{si.mcclean,bw.scotney}@ulster.ac.uk

[3] Department of Psychology, Utah State University, Logan, UT 84322-4440, USA
{chelsea.saunders,maria.norton,joann.tschanz}@usu.edu

[4] Population Sciences, Huntsman Cancer Institute, University of Utah, Salt Lake City, UT 84112, USA
ken.smith@fcs.utah.edu

Abstract. In this paper we study the use of medical history information extracted from the Utah Population Database (UPDB) to predict adoption of a reminder solution for people with dementia. The adoption model was built using 24 categorised features. The *k*NN classification algorithm gave the best performance with 85.8 % accuracy. Whilst data from the UPDB is more readily available than that in our previous work, the results highlight the benefit of including psychosocial and background information within an adoption model.

Keywords: Technology adoption · Prediction modelling · Assistive technology · Dementia

1 Introduction

The rising numbers of older patients aged 65 and above are putting a massive strain on current social and health care systems [1]. The rise in the number of older patients leads to an increase in workload for caregivers and an increase in the demand for the number of hospital beds. The challenges of caring will consequently become larger in the near future with limited facilities. Nevertheless, decentralization of healthcare coupled with the willingness of older patients to stay at home have led to developments in the area of assistive technologies [2]. The aim of these tools is to provide assistance through technology-based solutions that can assist in performing activities, remote healthcare assessments and monitoring and managing social interactions. The success of these tools are highly dependent on the acceptance by the target end users. It is therefore vitally

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important to understand the factors that affect technology adoption to make it successful in the long-term. Incorporating such information into prediction models that predict adoption has proved to be valuable and is a relatively new area of research.

Considering these challenges, our research aims to investigate the factors that affect technology adoption with a specific focus on reminding technologies for persons with dementia (PwD) [3]. In the related work on this area, we identified multiple features that impacted on PwD's decision in adopting video based reminding technology [4, 5], and a mobile-based reminder app [6]. The current work studies medical history features from the UPDB and considered how these affect the rate of adoption. The remainder of the paper is organised as follows: related work is discussed in Sect. 2; Sect. 3 describes the methodology used in the current study. Section 4 details the results attained from the adoption modelling and finally, Sect. 5 provides details of the conclusion to the work and possible future work.

2 Related Work

With the aim of modelling factors that affect acceptance of technology, it has been found that a limited amount of research has been carried out in this area. The psychosocial impact of assistive device scale (PIADS) [7] and technology acceptance model (TAM) [8] have been developed for modelling adoption of technologies. TAM is based on reasoning action and work under the assumption that user behavior is subjective to the perceived usefulness and ease of use. Nevertheless, the perceived usefulness of a particular technology may differ due to context of use, an individual's background and type of technology. PIADS is an extension of TAM and includes personal factors as well as external factors, for example people and society that may have an impact on usage. As a further extension to these findings, the unified theory of acceptance and use of technology (UTAUT) [9] has been developed that incorporates more reliable factors into the model. Following the evaluation of UTAUT, it was found that gender, age, experience and willingness to use directly affected adoption whereas attitude, self-efficacy and anxiety did not affect adoption. A Mobile Phone Technology Adoption Model (MOPTAM) has been built by integrating TAM and the influential factors from UTAUT. The MOPTAM has been used to model personal phone usage in university students. Preliminary evidence has been found in recent studies that different age groups follow a different approach to the use of technology and its subsequent adoption [10]. Older people realise the benefits of technology, however, consider themselves less capable of using technology based solutions [11]. As a result they report negative impact on themselves such as technology anxiety and lower self-efficacy [12]. It has also been found that older people have less interest towards high end technology products, however, have an appreciation for simple technology products that are easy to use, convenient to learn with additional features of safety and security [10]. It has been reported that technologies that assist in completing activities and convenient to use leave a positive impact on older people [11]. Factors influencing acceptance of technologies was studied in [13] and it was found that the factors affecting the acceptance were mostly studied in the pre-implementation stage.

Taking into consideration these findings the rationale to determine factors that affect adoption and how these could be improved so as to avoid negative outcomes and misuse of resources becomes increasingly important. Limited research has been undertaken to explore the factors that affect technology adoption among PwDs and their caregivers. In our previous research we identified that features such as gender, age, profession, experience, Mini-mental State Exam (MMSE) score, mobile reception, living arrangement and access to broadband were influential in an individual decision to adoption [4, 5]. Building on this work the Technology Adoption and Usage Tool (TAUT) project analysed data from the Cache County Study on Memory and Aging (CCSMA) [14] for participants who agreed to engage with a mobile based reminding solution [3]. The CCSMA dataset has a rich set of features consisting of patient medical data and self-proclaimed information, which was collected through consultation with the participant. Through undertaking analysis on this dataset it was found that the prediction of technology adoption could be achieved with a prediction accuracy of 92.48 % [15]. The aim of the current study is to model technology adoption using objective medical history information relating to the participants which was gleaned from the UPDB and subsequently study the impact of medical history on adoption of technology.

3 Methodology

The TAUT project actively engaged participants from the CCSMA to undertake the evaluation of TAUT reminder app for 12 months. For each participant additional information relating to their medical history was available from the UPDB dataset. This data was analysed in the current work. The current evaluation is based on a cohort of 169 subjects who were screened and contacted by the research team. Following this exercise 30 subjects met the inclusion criteria and agreed to participate in the study. For the purposes of the study a class name ‘adopter’ was used to represent those engaging with the app (consisting 30 recruits) and a ‘non-adopter’ class (containing the remaining 139 subjects contacted) was used to represent the remainder.

3.1 UPDB Dataset

The UPDB at the University of Utah is a rich dataset comprising information relating to the genetics, genealogy, demography, epidemiology and public health of the citizens within Utah. At present it contains information on approximately nine million people within the state of Utah. Participants from the CCMSA were linked to the UPDB, a procedure approved by the IRB of the University of Utah. From this dataset we considered information about the number of times a TAUT participant was hospitalized in the category of inpatient discharge/hospitalizations (HOSP) and Ambulatory Surgery (AS) from 1996 to 2013 for the 10 most prevalent diseases (Heart disease, Cancer, Chronic lower respiratory diseases, Accidents, Stroke (cerebrovascular diseases), Alzheimer disease (AD), Diabetes, Influenza/Pneumonia, Nephritis/nephrotic syndrome/nephrosis and Septicemia). Considering the huge number of features in the dataset, reduction of features was managed by merging features as follows: (1) Total year of Hospitalization

(Total HOSP), (2) Total year of Ambulatory Surgery (Total AS), (3) Total year of all 10 disease (HOSP + AS), (4) Recent three years of HOSP (5) Recent three years of AS and (6) Recent three years for all disease (HOSP + AS). The feature reduction resulted in a total of 24 features, providing information relating to the number of times a participant was hospitalized in each category.

3.2 Modelling Adoption

Each of the features in the UPDB dataset has continuous values resulting in a number of categories, hence posing challenges for the development of the prediction models. As a solution to this problem, the variables were discretized [15]. We categorized each feature into fewer categories. For example, Total AS feature that represents the total number of times a participant was hospitalized in ambulatory surgery was categorized into fewer categories of NoneAS, FewAS and LotAS based on 0 times, 1 to 5 times and more than 5 times respectively. To find the best model that can predict adoption we considered a range of classification algorithms following our previous work reported in [4]. The algorithms considered were: C4.5 Decision Tree (DT), Neural Network (NN), Support Vector Machine (SVM), *k*-nearest-neighbour (*k*NN), Adaptive Boosting (AB), Naïve Bayes (NB) and Classification and Regression Trees (CART).

4 Results

Following the resampling of the UPDB dataset, the new data were used to build the prediction models by applying classification algorithms described in the previous section. The UPDB dataset consisted of 139 non-adopters and 30 adopters. Such an imbalance in the dataset may lead to bias towards the majority class [4, 5]. To handle the imbalance in the dataset the Synthetic Minority Over-Sampling Technique (SMOTE) was applied. Following application of SMOTE the adopter minority class was given a 363 % (100*(139−30)/30) boost to make it equivalent to the non-adopter class. Each model was built with 24 labelled features. SMOTE was only applied to the training dataset. Original data was used for testing. This gave us the chance to predict the model's performance in real world scenarios where the given dataset may have had imbalance. Table 1 presents average prediction accuracies of the models built with the SMOTE data and tested on the real data for a range of algorithms. In comparison to the results obtained for the CCSMA dataset, the results obtained for the UPDB dataset have lower accuracy. In the CCSMA dataset with a reduced set of labeled features, it was possible to differentiate between the non-adopters and adopters with an average prediction accuracy of 92.48 % for the *kNN* model [15]. Although the results using only the UPDB do not perform as well as the data collected from the cohort using the reminder app, the results indicate that from the technology side there is merit to consider the integration with other data for the purpose of modelling adoption.

Table 1. Average prediction accuracies (%) of the models learnt.

Dataset	NN	C4.5 DT	SVM	NB	AB	*k*NN	CART
All 24 features SMOTE model + test original data	84.02	74.56	72.78	59.17	66.86	85.80	77.25

5 Conclusion and Future Work

The acceptance of technology based assistive solutions is critical for their long term success. In this paper we studied the UPDB dataset in an effort to understand the impact of medical history of a patient's likelihood to adopt a technology based service. The prediction model was built using 24 features on a SMOTE dataset and was tested on the original data. Taking into consideration only the medical history, the *k*NN classification algorithm gave the best performance of 85.8 % accuracy. The UPDB dataset is unique in itself, however, it requires more information about the individuals. It would be useful to merge the CCSMA and the UPDB dataset together so that the prediction models have both information related to (1) user background such as age, gender, profession and (2) medical history. The inputs from these datasets could lead to the development of a better technology adoption model. Future work will be undertaken to merge these datasets and to subsequently find a sub-set of features that could model adoption more effectively.

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