

Technology Adoption and Prediction Tools for Everyday Technologies Aimed at People with Dementia

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Abstract— A wide range of assistive technologies have been developed to support the elderly population with the goal of promoting independent living. The adoption of these technology based solutions is, however, critical to their overarching success. In our previous research we addressed the significance of modelling user adoption to reminding technologies based on a range of physical, environmental and social factors. In our current work we build upon our initial modeling through considering a wider range of computational approaches and identify a reduced set of relevant features that can aid the medical professionals to make an informed choice of whether to recommend the technology or not. The adoption models produced were evaluated on a multi-criterion basis: in terms of prediction performance, robustness and bias in relation to two types of errors. The effects of data imbalance on prediction performance was also considered. With handling the imbalance in the dataset, a 16 feature-subset was evaluated consisting of 173 instances, resulting in the ability to differentiate between adopters and non-adopters with an overall accuracy of 99.42 %.

I. INTRODUCTION

The increasing numbers of the population aged 65 and over are placing a huge strain on today's health and social care systems [1]. As a result, society has now reached a situation where there is an increasing number of dependent elders who require a form of personalized care and in some instances require resettlement from their own homes into a form of institutionalized care. It has, however, been recognised that through the use of home-based technologies, the period of time an older person can remain at home can be extended [2]. A secondary effect of such technology based solutions is the reduction in burden they offer to healthcare systems and caregivers. Examples include the use of technology to assist with activities of daily living, to facilitate remote assessment, to provide task prompting and

to promote social interactions. A growing area of research in assistive technologies involves the development of assistive tools that can help to support cognitive functioning of an elderly person and/or those suffering from a mild cognitive impairment or early stages of dementia [3, 4]. These solutions are, however, only beneficial if they are fully embraced and used by the target end users. A key requirement in the design of assistive technologies is the understanding of the factors that contribute to the user's decision of using the assistive technologies, or more commonly referred to as technology adoption modelling. A prediction model that could help in the early stage assessment of the likelihood of adoption of assistive technologies could assist in avoiding negative experiences with technology usage and identify those users who are most likely to have a positive experience and benefit from the introduction of an assistive solution into their lives [5, 6].

Considering these challenges, our research focuses on exploring the factors, which effect adoption of assistive technologies, specifically reminding technologies for persons with dementia (PwD) [7]. In our previous work we identified a number of features which impacted on a PwD's decision to adopt a video based reminding technology [5, 6]. The current paper builds upon our findings towards identifying a refined sub-set of features, which offer improved accuracy in predicting technology adoption. The remainder of the paper is organized as follows: related work is discussed in Section 2. The methodology and the approach adopted for adoption modeling in the current study are described in Section 3. Section 4 provides details of the evaluation performed. Finally, Section 5 provides the conclusion to the work and describes areas of planned future work.

II. RELATED WORK

Efforts have been made in past to understand the factors that define prediction of assistive technologies. Models such as the technology acceptance model (TAM) [8] and psychosocial impact of assistive device scale (PIADS) [9] have been developed for predicting technology adoption. TAM is based on reasoned action and assumes that the user behavior is influenced by the perceived usefulness and ease of use. Nevertheless, the perceived usefulness of an assistive technology may vary due to diversity in context, technology and an individual's background. The PIADS solution is an extension of TAM. This approach focuses on personal factors and also takes into consideration the existence of

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external factors such as people and society that may have an impact on usage and self-image. For incorporating more reliable factors into the model, a broad unified theory of acceptance and use of technology (UTAUT) was developed [10]. Apart from considering perceived usefulness, the UTAUT identifies three direct determinants of intention of usage (performance expectancy, effort expectancy, and social influence), two direct determinants of usage behavior (behavioral intention and facilitating conditions), and incorporates four moderators (gender, age, experience, and voluntariness of use). Based on the evaluation of UTAUT, it was found that features such as age, experience, gender and willingness to use had a direct impact on adoption whereas self-efficacy, attitude and anxiety had no effect on adoption. Another model built by integrating TAM with mediating factors from UTAUT is Mobile Phone Technology Adoption Model (MOPTAM). The MOPTAM has been used to model the personal mobile phone use in university students [11].

More recent studies provide preliminary evidence that different age groups may think differently and make different decisions when it comes to the adoption and use of technology [12]. Specifically, findings indicate that while older people appreciate the benefits of technology they often perceive themselves as not possessing the required skills and are not sure of its benefits as they may consider themselves not skilled enough to use these kinds of high-technology applications [13]. Consequently, they report lower self-efficacy and higher technology anxiety [14]. It has been noted that older people do not show interest in high-technology products, however, rather value the technology that can make their daily life easier and provide added safety and security [12]. A positive impact on older people is most frequently associated with how the technology supported activities, enhanced convenience and contained useful features [13]. A systematic study of the factors influencing the acceptance of electronic technologies that support aging in place by community-dwelling older adults was carried out in [15]. It was found that a qualitative study of factors affecting the acceptance of technology is mostly studied in the pre-implementation stage. Acceptance in the pre-implementation stage is influenced by 27 factors, divided into 6 themes: concerns regarding technology (e.g., high cost, privacy implications and usability factors); expected benefits of technology (e.g., increased safety and perceived usefulness); need for technology (e.g., perceived need and subjective health status); alternatives to technology (e.g., help by family or spouse), social influence (e.g., influence of family, friends and professional caregivers); and characteristics of older adults (e.g., desire to age in place). Nevertheless, in the post implementation stage some factors persist while new factors also emerge. For predicting mobile phone adoption by the elderly, a Senior Technology Acceptance & Adoption model for Mobile technology (STAM) was developed in [16].

With the collective interest and increasing research in determining adoption in elderly patients [5], it is therefore

desirable to have a broader insight into how technology adoption may be further improved. To date, limited efforts have been directed towards technology adoption for PwD and their carers. Our previous research in the area of technology adoption modeling identified features such as age, gender, Mini mental state exam (MMSE) score, profession, technology, experience, access to broadband, mobile reception and living arrangement to be relevant to adoption [5, 6]. The aim of the current study is to extend upon our previous findings and identify a subset of features which will assist in increasing the performance of technology adoption modeling. In addition, the effects of different computational approaches and managing the imbalance in the available data will also be considered.

III. METHODOLOGY

This research was conducted within the TAUT project which aims to engage with PwD associated with the Cache County Study on Memory in Aging (CCSMA) [17]. Each participant was enrolled on a 12 month evaluation study of the TAUT reminder application (app) described in [7] and presented in Figure 1. The app benefits from 10 years of experience in the design, implementation and evaluation of assistive cognitive prosthetics. This system has been designed by a multidisciplinary team through an iterative design process and has been previously evaluated on a small scale with a representative cohort [6]. The current version of the app, described in [7], is developed for the Android platform and is designed to provide the user with an interface to schedule and acknowledge reminders for a range of daily activities including, medication, meals, appointments and bathing. The reminders can be set by the PwD, or by a caregiver or family member and are delivered at the time specified and presented as a popup dialog box on screen accompanied by a picture indicating the type of ADL, a textual description and a melodic tone.

Figure 1. Screenshots from the TAUT app showing: (a) A reminder popup (b) Upcoming reminders list (c) Reminder creation screen.



In the present evaluation, 173 people were screened and contacted by the research team. Following this exercise 21 people were eligible and agreed to engage in the study. An ‘adopter’ class (consisting 21 recruits) and a ‘non-adopter’ class (containing the remaining 152 people contacted) was established. In our previous work [18] with the CCSMA dataset, representing a large set of features, 31 features were used to model adoption and non-adoption. The features covered a range of criteria including: age, gender, MMSE score, employment and details of a range of health conditions.

The CCSMA data used in our previous work had 31 features, which is a large feature set, and therefore, from an

information engineering perspective, it is considered that all the features may not be required to accurately model the adoption process. The process of feature selection is performed to reduce the dimensionality of the original feature vector whilst still maintaining the same, or improved, levels of accuracy with the technology adoption modeling. A reduction in the numbers of features has the additional benefit of reducing the computational complexity of the adoption model itself. As a means of feature selection and to find features that are directly related to the adoption, specifically, a pair-wise significance test was performed on each individual feature against the output class. A Chi-square test was performed in IBM SPSS Statistics 22.0.0. Based on the p -values the original set of 31 features was reduced to 16 features, as detailed in Table 1.

TABLE 1: SET OF 16 FEATURES USED IN STUDY.

Personal	Genetic	Comorbidity
Gender	APOE Genotype	Diabetes self-endorsed
Age	APOE4 copy number	Heart attack self-endorsed
Education	Any variant of APOE4	Stroke self-endorsed
Job	Dementia	Hypertension self-endorsed
Observation	Dementia code AD pure	High Cholesterol self-endorsed
Last CCSMA observed	Dementia code Any	
CCSMA observed date		

A. Learning adoption models

To develop the most suitable model for predicting adoption, different data mining algorithms are evaluated for their suitability in the prediction task against the select feature set. A range of popular data mining algorithms were selected; namely: Neural Network (NN), C4.5 Decision Tree (DT), Support Vector Machine (SVM), Naïve Bayes (NB), Adaptive Boosting (AB), k -nearest-neighbour (k NN), and Classification and Regression Trees (CART).

B. Handling imbalanced classes

An imbalance in datasets can lead to a bias towards the majority class. Given the imbalance in the data used in the current study, we investigated how the prediction performance of the adoption models were affected by addressing the issue of data imbalance. To address the imbalance in the dataset, Synthetic Minority Over-Sampling Technique (SMOTE) was applied. The proportion of the data distribution was approximately 88% non-adopters and 12% adopters. The adopter minority class was given a 624% ($100 \times (152-21)/21$) boost to make it equal to non-adopter class. This was performed to equalize the chance of the percentage of adopters being misclassified as non-adopters and the percentage of non-adopters being misclassified as adopters. The resampled data therefore consisted of 152 adopters and 152 non-adopters.

IV. DEVELOPMENT OF ADOPTION MODELS

Model performance was evaluated in terms of class prediction and prediction bias among classes. The models were evaluated on the overall prediction accuracy, F-measure

and the difference between the two types of errors (false positive and false negative classifications).

A. Model Prediction Performance

In the first scenario, models were derived on the original data without handling the data imbalance for both the 31 and 16 feature set data. In the second scenario, the SMOTE was applied only on the training dataset and the resulting models were tested on the original data. This gives the chance to evaluate the model performance in real world scenarios, where there may be imbalances in the observed data. The prediction performances were compared between models derived using the same classification algorithm, on data with the two different feature sets of 31 features and 16 features. Table 2 presents average prediction accuracies for the models, with 31 and 16 feature sets learnt, respectively and tested for both the scenarios over a range of algorithms.

TABLE 2: AVERAGE PREDICTION ACCURACIES (%) OF THE MODELS WITH 31 AND 16 FEATURE SETS LEARNT ON ORIGINAL AND RESAMPLED DATA AND TESTED ON THE ORIGINAL DATA OVER A RANGE OF ALGORITHMS.

	31 feature original train + test (%)	16 feature original train + test (%)	31 feature SMOTE model + original test (%)	16 feature SMOTE model + original test (%)
NN	76.3	78.61	97.69	97.10
DT	86.13	86.13	86.70	94.80
SVM	87.86	87.86	64.16	59.54
NB	41.04	69.36	40.46	36.42
AB	86.70	85.55	73.41	81.50
kNN	77.46	78.61	90.17	99.42
CART	87.28	87.86	91.91	90.75

For the models built and tested on the original data, the 31 and 16 feature sets provided similar accuracies for almost all the models considered. When the models are built on resampled data and tested on original data, the 16 feature set k NN model outperform all the other models. This result is encouraging, as with a smaller number of features in the predictive model, not only will it be easier to collect, it also reduces the model's computational complexity in learning and more importantly in making a prediction. The effect of resampling the minority class data to handle data imbalance, in terms of the prediction performances of the models is also investigated. It is to be noted that in comparison to our previous work [18] where the built model was tested with 31 attributes and three classifiers along with data imbalance, the current results are improved. With the 31 feature set, the F-measure was DT = 0.79, k NN = 0.71, and NB = 0.42, and with 16 feature set, the F-measure index was DT = 0.85, k NN = 0.77, and NB = 0.39

The ease of use and the outcomes of the built prediction models become significantly important features for these kinds of healthcare based applications. DTs are particularly beneficial in healthcare-based applications as the decision making process is transparent and can be visualised as trees [5]. The k NN-based models work on the concept of finding the nearest neighbour for the unknown case based on the similarity measure between the unknown case and its

neighbours. This aspect of k NN makes its useful for healthcare professionals. Based on the observed feature values for the unknown case, the output from the prediction model can be correlated by the health care professional based on their previous experience in a similar kind of set-up with a PwD. Contrary to this the output from more complicated models such as SVMs and NNs are a challenging task for non-technical professionals.

B. Model Prediction Bias

The model prediction bias on the two imbalanced classes was subsequently evaluated. Model prediction bias toward the majority class can be a critical issue. Table 3 provides a comparison of the average prediction errors obtained between models trained on data with and without SMOTE, for both dataset of 31 and 16 features, respectively.

TABLE 3: PREDICTION ERROR DIFFERENCE COMPARISON WITH AND WITHOUT SMOTE FOR MODELS TRAINED ON DATA WITH 31 AND 16 FEATURES, RESPECTIVELY.

Models	Type I error	Type II error	Difference
Models with 31 features + SMOTE	0.130 0.208	0.863 0.287	0.733 0.079
Models with 16 features + SMOTE	0.078 0.199	0.931 0.206	0.852 0.007

As can be viewed from Table 3, in both scenarios, the prediction bias toward the majority class has been reduced using the data resampling approach on the training data. Hence the difference between the false positive and false negative classification is reduced.

V. CONCLUSION AND FUTURE WORK

The acceptance of assistive technologies is critical to their success. In this paper, we characterized features that are useful in profiling adopters and non-adopters. Based on these features, an optimal predictive model was developed by exploring a range of classification algorithms, different feature sets, and data resampling to handle class imbalance. The models were evaluated using the multiple criteria of model predictive performance, prediction robustness and bias toward two types of errors. Overall, the model trained using the k NN classification algorithm with the 16 feature set gave the best performance with 99.42 % accuracy.

These predictive models can maximize the opportunity of using assistive technology with the intention of allowing PwDs to stay in their home independently for longer periods of time. In the current work the feature set was reduced from 31 to 16 features. Collecting features may be expensive and time-consuming, therefore it is required to reduce the feature set size more while still keeping the prediction accuracy high. A possible future pointer in this work would be to reduce the size of feature set further for more accurate prediction.

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