

A Knowledge-Driven Approach to Predicting Technology Adoption among Persons with Dementia

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Abstract—As the demographics of many countries shift towards an ageing population it is predicted that the prevalence of diseases affecting cognitive capabilities will continually increase. One approach to enabling individuals with cognitive decline to remain in their own homes is through the use of cognitive prosthetics such as reminding technology. However, the benefit of such technologies is intuitively predicated upon their successful adoption and subsequent use. Within this paper we present a knowledge-based feature set which may be utilized to predict technology adoption amongst Persons with Dementia (PwD). The chosen feature set is readily obtainable during a clinical visit, is based upon real data and grounded in established research. We present results demonstrating 86% accuracy in successfully predicting adopters/non-adopters amongst PwD.

I. INTRODUCTION

It is estimated that between the years 2010 and 2050 the number of Persons with Dementia (PwD) will increase over threefold from 35.56 million to 115.38 million [1]. This increased worldwide prevalence of dementia may be, in part attributed to increased life expectancy [2], the levels of middle-age obesity [3] and viruses such as HIV [4].

One common symptom of dementia is short-term memory loss which may impact upon an individual's ability to perform common Activities of Daily Living (ADL) such as eating appropriately or taking medicine. Due to the progressive nature of dementia such symptoms may become increasingly severe eventually resulting in the PwD requiring institutionalization in an appropriate care facility. Whilst such a measure may be necessary in later stages of dementia to promote the safety of the PwD-Caregiver dyad there are two primary reasons why institutionalizing of PwDs should be deferred as long as possible. Firstly, patients with *mild* dementia may have a higher quality of life (psychological, physical, social and environmental) when receiving home-based as opposed to facility-based care [5]. Furthermore where the caregiver is a family member the transition between care types may not necessarily decrease anxiety and, in some cases leads

to an increased risk of clinical depression [6]. Secondly, from a financial perspective caring for a person with mild dementia in the community is considerably less expensive than dementia care in a residential environment [7].

An emerging approach to ensuring that a PwD can remain in home-based care as long as feasible is through the use of assistive technologies that specifically address the short-term memory impairment experienced by PwDs. One such technology is the Mobile Phone based Video Streaming (MVPS) system [8] which aims to function as a *cognitive prosthetic* for a PwD. The MVPS system consists of a mobile phone capable of receiving and playing video-based reminders. Video reminders are recorded and uploaded to a secure database by the caregiver along with schedule information and associated meta-data, for example the type of the reminder. The MVPS system periodically checks the database for reminders and downloads collections of future reminders that are scheduled for a given time frame. The modified handset is equipped with a single 'OK' button which is used to acknowledge receipt of the reminder.

Whilst assistive technologies have the potential to enable a PwD to remain at home for as long as possible this benefit is intuitively predicated upon the successful interaction and ultimate adoption of such technologies. Moreover, imposing inappropriate types of assistive technologies upon unwilling or unsuitable PwDs may ultimately have a detrimental effect upon their overall well being. This detrimental effect may be caused by the PwD being unfamiliar with the technology and therefore feeling overwhelmed or afraid of making mistakes. Thus in order to ensure that appropriate types of assistive technologies are given to those whom it will benefit, it is necessary to successfully predict *adopters* and *non-adopters*.

A. Related work

Within the literature there are various models which attempt to address the notion of predicting technology adoption. One such example is the work in [9] where Venkatesh et al. (2003) present the Unified Theory of Acceptance and Use of Technology (UTAUT) model which integrates key constructs from eight previously proposed models: the theory of reasoned action, the technology acceptance model, the motivational model, the theory of planned behaviour, a combination of the technology acceptance model and the theory of planned behaviour, the model of PC utilization, the innovation diffusion theory and social cognitive theory. Constructs and moderating variables that were shown to be statistically significant in predicting the intention to use

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were chosen for inclusion within the UTAUT model. The UTAUT model was empirically evaluated using technology acceptance data from four organizations in different business areas and found to outperform each of the eight individual models. Overall, the UTAUT model was able to account for 70% of the variance in usage intention in comparison to the highest achieved (53%) for a single model (TAM2).

The UTAUT model was extended by Heerink et al. (2010) [10] resulting in ‘The Almere Model’. In order to obtain generalizable findings Heerink et al. performed experiments using different systems namely, assistive robots and screen agents located in user’s homes and eldercare institutions. Additional constructs that were added to the UTAUT model included the concept of anxiety in addition to incorporating a patient’s attitude towards the technology. Due to the application of assistive robotics the Almere Model includes constructs which are primarily pertinent to such a deployment, for example the social presence of the robot and perceived sociability. The final Almere Model has ten constructs with a Goodness of Fit Index of .96.

One issue with utilizing general prediction models for PwDs is that they are heavily reliant upon constructs which are subjective, for example ‘perceived usefulness’ [10] or ‘performance expectancy’ [9]. These constructs are typically measured by a patient’s response to relevant questions using a predetermined scale. However, the response to such constructs may be influenced by the patient’s state on the day of questioning rather than accurately reflecting their longitudinal attitudes. The main novelty of this paper therefore lies in proposing a set of knowledge-based features (i.e. variables) for predicting technology adoption among PwD. In comparison to features which are primarily subjective such as ‘intention of use’ the chosen knowledge-based feature set principally consists of variables describing a patient’s profile, such as age, gender, Mini Mental State Examination (MMSE) and technical experience in addition to two readily obtainable environmental features, namely the quality of mobile reception and the PwD’s living arrangement. We extend our previous work in [11] and [12] subsequently choosing a feature set which yields higher classification performance and is grounded in well-established clinical research such as that presented in [13].

The remainder of this paper is structured as follows: in Section II we utilise both statistical and wrapper based feature selection techniques subsequently choosing a knowledge-based feature set. In Section III we show from the literature how each variable in the chosen set influences technology adoption. In conclusion, results and future work are presented in Section IV.

II. FEATURE SELECTION

The process of feature selection is used to identify a subset of features from the overall set which has a high discriminatory ability. Given the application of predicting technology adoption among PwD during a clinical consultation it is necessary to select features which are readily obtainable thus helping to alleviate undue stress upon the PwD or their carer.

Furthermore, it is desirable to choose a subset which has relatively few elements. This has two benefits: firstly, the time taken to collect the actual features may be reduced. Secondly, due to the ‘curse of dimensionality’ the number of features directly impacts both upon the necessary amount of training data and the time taken to learn a classification model. Within this subsection we utilize both a statistical and wrapper method of feature selection subsequently leading us to choose a subset of features to be used when classifying PwD into an output class.

The overall feature set was collected during longitudinal field trials of the MVPS system conducted with a cohort of 40 PwD/Caregiver dyads over 5 weeks [8]. At the end of the trial period, questionnaires were administered. These questionnaires were designed by a multi-disciplinary group including biomedical engineers, computer scientists, research nurses and geriatric consultants and aimed to gather information which could be used in the prediction of adopters/non-adopters. The response to questionnaires were subsequently used in conjunction with data obtained from the MPVS database and visit logs to create a feature set which contained {Age, Gender, MMSE, Previous profession, Prior technology experience, Broadband installation, Quality of mobile reception, Carer involvement, Living arrangement, Extra support, Physical health}. The output class of adopter/non-adopter was derived from the dyad’s response to a 4-item Likert scale which aimed to measure their level of adoption. Dyads who ‘dropped out’ or were considered ‘non-compliant’ were assigned membership of the non-adopter output class. Conversely, those who were ‘compliant’ or indicated that they would be ‘eager to keep the technology’ were assigned membership of the adopter class.

A. Statistical feature selection

As an initial step towards identifying a suitable set of features a correlation test was conducted between each available feature and the output class. This test enables the strength and statistical significance of the relationship between each predictor variable i.e. each feature and the output class to be determined. Subsequently, features with a statistically significant correlation with the output class are likely to have high predictive ability. and may therefore be used as input variables within a regression model. The correlation test indicated that five of the eleven features were correlated with the adopter/non-adopter class. Three of these features were relevant to a patient’s profile namely age, prior technical experience and MMSE. The further two features described a patient’s environment, specifically living arrangement and the presence of broadband.

Age had a negative correlation with the adopter/non-adopter output class with $r = -.407$, $\rho = .009$. Such a correlation is intuitive and in agreement with studies focusing on predicting technology adoption for the wider population, for example Czaja et al. (2006) [14]. Technical experience had a correlation of $r = .311$ and was nearly significant with $\rho = .051$. As the level of relevant, prior technical experience has been widely demonstrated within

the literature to influence technology adoption for a broad demographic group [13], [15], [16] we include this feature as an input to the prediction model. MMSE had a positive correlation $r = .406$ ($\rho = .009$) indicating that patients in a higher MMSE category (i.e. those with milder forms of dementia) were more likely to adopt assistive technology.

The environmental variable ‘living arrangement’ had a correlation of $r = .431$ ($\rho = .005$) suggesting that living with another person increased a patient’s likelihood of adoption. However, this may be largely dependant upon the profile of the patient’s living partner and could therefore be a phenomenon of this particular dataset. The presence of broadband had a positive correlation of $r = .435$ ($\rho = .005$). Where the primary caregiver lives with the patient the presence of broadband is a practical, environmental feature which enhances the overall usability of the MPVS system by reducing the time taken to upload videos and set reminder details. Additionally, the presence of broadband may be a proxy feature representing underlying attitudes, for example awareness of technology or a patient’s enthusiasm for change with respect to new technology.

Features which had a significant correlation with the output class were subsequently used as input to a logistic regression model. The generated logistic regression model was significant ($\rho = .0002$) and had a Nagelkerke R^2 value of .604 indicating that the model provides a reasonable fit of the data. The features Age and MMSE were the only predictor variables for which a unit change resulted in a statistically significant increase in the odds ratio. The overall prediction accuracy of the model was 82.5% with 92.9% of adopters being correctly predicted in comparison to 58.3% of non-adopters. There was an overall false positive rate of 12.5% and a false negative rate of 5%.

For our application of predicting adopters/non-adopters of assistive technology among PwD there are negative consequences associated with both types of error which may impact upon the personal well-being of both the PwD and their caregiver. Incorrectly classifying a PwD as an adopter (i.e. a false positive) and subsequently prescribing them assistive technology may have a detrimental impact upon the dyad by, for example causing undue anxiety or stress. On the other hand incorrectly assigning a PwD into the non-adopter class (i.e. a false negative) may ultimately deprive the PwD of an opportunity to remain in their own home for as long as possible. We therefore conduct wrapper-based feature selection to identify a subset of features which yield a high classification accuracy whilst reducing the two types of errors. The features *Age* and *MMSE* are used as a start set for the wrapper-based method as they have been found to have statistically significant predictive abilities for this dataset.

B. Wrapper-based feature selection

Due to the relatively small cohort size of $n = 40$ we performed wrapper based feature selection to enable the identification of features which, whilst not statistically significant for our dataset may be influential in predicting technology adoption within real-world situations. Wrapper

based methods of feature selection employ the classification algorithm to be used as a method of evaluating the impact a feature has upon the overall accuracy of the model. For this stage of feature selection we utilized a k NN classifier which was shown by Zhang et al. (2013) [11] to provide high classification accuracy in addition to yielding an output which may be readily understood by healthcare professionals.

A best first search of the feature space was conducted which performed greedy hill climbing with optional backtracking. The PwD’s age and MMSE score was used as a start set as it was found in the previous subsection to have a significant influence upon the output class. This wrapper based approach yielded the following feature set $\{Age, Gender, Mobile\ reception, MMSE, Living\ arrangement, Physical\ health, Technical\ experience\}$. In order to ensure the clinical relevance and potential generalizability of this feature set we present evidence from the literature as to why each of the person-centric variables influence technology adoption within the following section.

III. CLINICAL SIGNIFICANCE OF SELECTED FEATURES

Gerontological and accessibility studies of age related changes in performance clearly show that age is correlated to gradual degradation of performance and the onset of specific functional deficits that impair performance [14], [17], [18]. In particular, it has been shown that age related cognitive deficits will impair the learning of new interfaces, and the overall rate of interaction [13]. It is clear that this will be related to prior technology experience, both recently acquired and generational in origin. The MMSE is sensitive to high levels of impairment due to its normalization on clinical populations; for example, high levels of impairment will be associated with extreme functional loss directly influencing technology adoption.

There is evidence that likelihood of continued use of new IT is moderated by gender related differences in nomethetic studies of motivational behaviour. For example, females, faced with new tasks can perceive them as beyond their competence and are sensitive to task performance feedback such that early failure acts as reinforcement for this attitude. This may be related to a perception of their own fixed capability limitations. Conversely, males have been shown to maintain confidence in capabilities for ultimate success and are not deterred by repeated early negative task feedback. This may also be age linked in that this effect has been demonstrated in older participants in games tasks, both in predicting actual performance and likelihood to continue use [19].

Health status is likely to be a proxy variable linked to technology adoption through general age related functional impairment and specific functional deficits resulting from early stages of dementia, such as cognitive process metrics like speed of processing, capacity of working memory and retrieval and accuracy of skills from long term memory [20]. In addition, reduced dexterity and physical movement will also reduce users capability of successfully interacting with a product and hence learning to use it.

The basic usability of new technology is a barrier to adoption. The importance of prior experience of similar technologies to interaction has been established in the appearance and functionality of controls and in prior exposure to branded styles or interaction clichés [13], [15]. In addition, a strong generational effect has been demonstrated such that users early experience of technology affect their expectations and capabilities [16].

The presence of a living partner could be significant because of the increased availability of assistance, physical and technical aid during early exposure of the user to IT interventions and the increased likelihood of positive task feedback and reduced interaction times. Adoption is likely to be related to comfort, interest and access, education and socioeconomic status [14].

IV. RESULTS AND FUTURE WORK

Within this section we present classification results using the feature set $\{Age, Gender, Mobile\ reception, MMSE, Living\ arrangement, Physical\ health, Technical\ experience\}$. Due to the relatively small sample size we employ n -fold cross-validation which splits the data (assuming randomization followed by stratification) into n separate folds. One fold is retained for use as a test set and the remainder used for training. The process is repeated n times until each fold has been used both as a train and test set and the results averaged to form an overall accuracy value. To ensure reliable results we repeat the cross-validation procedure over 1000 runs.

By utilizing a k NN classifier with 1 neighbour and 4-fold cross-validation we achieved an average accuracy of 86.24%. There was a false positive rate of 2% in comparison to 11% false negatives. In an application such as predicting technology adoption amongst PwDs there are costs associated with both types of errors: for example, a false positive may result in a PwD being erroneously assigned assistive technology thus incurring the monetary cost of deployment in addition to having a potentially negative impact upon the well-being of the PwD. On the other hand a false positive may deprive an adopter of the chance to remain in their own home for an extended period of time.

One method of addressing class imbalance when developing a predictive model is through the use of the Synthetic Minority Oversampling Technique (SMOTE). When SMOTE was incorporated the overall accuracy fell to 77.82% with 11.56% false positives and 10.58% false negatives, thus achieving similar results for the two classes at the expense of overall accuracy.

Whilst the results were obtained using a relatively small sample size of $n = 40$ they nevertheless represent potential in our proposed feature set which is grounded in multi-disciplinary research and may be readily obtained during a clinical visit. With this in mind, a key part of future work will therefore be to evaluate our knowledge-based feature set on a larger sample size thus further demonstrating its applicability to predicting technology adoption amongst PwD in real-world scenarios.

REFERENCES

- [1] Martin Prince, Renata Bryce, Emiliano Albanese, Anders Wimo, Wagner Ribeiro, and Cleusa P Ferri. The global prevalence of dementia: a systematic review and metaanalysis. *Alzheimer's & dementia : the journal of the Alzheimer's Association*, 9(1):63–75.e2, January 2013.
- [2] Aronson MK, Ooi WL, Geva DL, Masur D, Blau A, and Frishman W. Dementia: Age-dependent incidence, prevalence, and mortality in the old old. *Archives of Internal Medicine*, 151(5):989–992, 1991.
- [3] Rachel a Whitmer, Erica P Gunderson, Elizabeth Barrett-Connor, Charles P Quesenberry, and Kristine Yaffe. Obesity in middle age and future risk of dementia: a 27 year longitudinal population based study. *BMJ (Clinical research ed.)*, 330(7504), June 2005.
- [4] Justin C McArthur, Norman Haughey, Suzanne Gartner, Kathy Conant, Carlos Pardo, Avi Nath, and Ned Sacktor. Human immunodeficiency virus-associated dementia: an evolving disease. *Journal of NeuroVirology*, 9(2):205–21, April 2003.
- [5] A. W. Nikmat, G. Hawthorne, and S. H. Al-Mashoor. The comparison of quality of life among people with mild dementia in nursing home and home care—a preliminary report. *Dementia*, pages 1–12, July 2013.
- [6] Richard Schulz, Steven H Belle, Sara J Czaja, Kathleen a McGinnis, Alan Stevens, and Song Zhang. Long-term care placement of dementia patients and caregiver health and well-being. *JAMA : the journal of the American Medical Association*, 292(8):961–7, August 2004.
- [7] Helen Crisp. *Spotlight on Dementia Care*. Number October. The Health Foundation, London, UK, 2011.
- [8] Mark Donnelly, Chris Nugent, Sally McClean, Bryan Scotney, Sarah Mason, Peter Passmore, and David Craig. A Mobile Multimedia Technology to Aid Those with Alzheimer's Disease. *IEEE Multimedia*, 17(2):42–51, April 2010.
- [9] V Venkatesh, Morris MG, Davis GB, and Davis FD. User Acceptance of Information Technology: Toward a Unified View. *MIS Quarterly*, 27(3):425–478, 2003.
- [10] Marcel Heerink, Ben Kröse, Vanessa Evers, and Bob Wielinga. Assessing Acceptance of Assistive Social Agent Technology by Older Adults: the Almere Model. *International Journal of Social Robotics*, 2(4):361–375, September 2010.
- [11] Shuai Zhang, Sally McClean, Chris Nugent, Mark Donnelly, Leo Galway, Bryan Scotney, and Ian Cleland. A predictive model for assistive technology adoption for people with dementia. *IEEE Journal of Biomedical and Health Informatics*, (c):1–1, 2013.
- [12] S O'Neil, McClean S.I., M.P. Donnelly, C.D. Nugent, L. Galway, T. Young, B.W. Scotney, S.C. Mason, and D Craig. Development of a Technology Adoption and Usage Prediction Tool for Assistive Technology for People with Dementia (In Press). *Interacting with Computers*, 2013.
- [13] P. M. Langdon, T. Lewis, and P. J. Clarkson. Prior experience in the use of domestic product interfaces. *Universal Access in the Information Society*, 9(3):209–225, August 2010.
- [14] Sara J Czaja, Neil Charness, Arthur D Fisk, Christopher Hertzog, Sankaran N Nair, Wendy a Rogers, and Joseph Sharit. Factors predicting the use of technology: findings from the Center for Research and Education on Aging and Technology Enhancement (CREATE). *Psychology and aging*, 21(2):333–52, June 2006.
- [15] A. Blackler, V. Popovic, and D. Mahar. The nature of intuitive use of products: an experimental approach. *Design Studies*, 24(6):491–506, 2003.
- [16] C. Wilkinson, P.M. Langdon, and P.J. Clarkson. Exploring Prior Experience and the effects of Age on Product Interaction and Learning. In *Human Computer Interaction International*, pages 457–466, Las Vegas, USA, 2013. Springer.
- [17] R. Haigh. The Ageing Process: A Challenge for Design. *Applied Ergonomics*, 24(1):9–14, 1993.
- [18] H. Petrie. Accessibility and usability requirements for ICTs for disabled and elderly people: a functional classification approach. In J.G. Abascal and C. Nicolle, editors, *Inclusive guidelines for human computer interaction*. Taylor and Francis, London, 2001.
- [19] Tanya Goldhaber, Patrick M. Langdon, and John P. Clarkson. Designing Intrinsically Motivating User Interfaces for the Ageing Population. *Universal Access in Human-Computer Interaction. User and Context Diversity*, 8010:68–77, 2013.
- [20] S.J. Czaja and C.C. Lee. Information technology and older adults. In J.A. Jacko and A. Sears, editors, *The Human Computer-Interaction Handbook*, pages 777–792. Lawrence Erlbaum Associates, New York, USA, 2 edition, 2008.