

# A MULTI-CRITERIA SORTING APPROACH FOR DIAGNOSING MENTAL DISABILITIES

Paulo Freitas<sup>1</sup>, Carlos Henggeler Antunes<sup>2</sup> and Jorge Dias<sup>1</sup>

<sup>1</sup>*Institute of Systems and Robotics, University of Coimbra, Coimbra, Portugal*

<sup>2</sup>*INESC Coimbra, University of Coimbra, Coimbra, Portugal*

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**Abstract:** A multi-criteria model tackled by an outranking method devoted to the sorting problem is presented to support decision making in assessing individual mental disabilities using information required in the Clinical Dementia Rating scale. This diagnosis process is a critical factor for adapting treatments to the current stage of the disease and improving health care and quality of life. The criteria required in the Clinical Dementia Rating scale have been considered as an input for developing our multi-criteria model, the output of which is the classification of each individual under evaluation in a pre-defined ordered class (category) as an indicator of the revealed level of mental disabilities. A method based on the exploitation of an outranking relation for the sorting problem is used to compare the individual information according to multiple evaluation criteria with reference profiles (specified standards) that define the boundaries of the classes. This methodological approach is substantially different from the ones based on the aggregation of the different criteria using weighted-sums to produce a “common value” measure. The method requires meaningful technical parameters, such as weights (herein perceived as true importance coefficients of the multiple evaluation aspects), distinct thresholds to ascertain the outranking classification, and a cutting level establishing the exigency of the classification. A realistic example using the decision support system Iris is presented to illustrate the results.

## 1 INTRODUCTION

Decision making processes are daily tasks associated with several contexts in people's life. In health care decisions, inadequate evaluations may lead to bad judgments and consequently result in inappropriate treatments and negative health effects. Therefore, sound models and methodologies shall be developed to support making the best decisions when handling with situations concerning people's health care in face of multiple, often conflicting, evaluation aspects. A specific area that requires feasible and reliable diagnosis is associated with dementia assessment and treatments. In these cases the diagnosis decision support process is generally divided in several stages and is based on multiple criteria to reach a comprehensive evaluation. This type of decisions is increasingly important due to the growth of life expectancy, which is accompanied by an increasing prevalence of health impairments and mental-health problems such as dementia (Hendrie, 1998). Early and accurate identification of

individuals who are at a high risk of developing dementia is regarded as a research priority. This identification followed by effective interventions may significantly contribute to reducing the prevalence and incidence of dementia diseases, improving the quality of life both of the patients and their caregivers, and making a more efficient use of the resources needed to provide adequate institutional and home health care. The process of early identification assumes even greater importance knowing that there are already treatments to help slowing the disease progression and prevention strategies including lifestyle changes (Roberson and Mucke, 2006). The DESCRIPA Study (Vissera et al., 2008) presents an evaluation over three years of a set of clinical criteria for further analysis of which variables best predict dementia, in particular Alzheimer's disease. Functional impairment in people in risk of dementia has been studied to understand what are the indicators associated with the disease's progress (Wilkins et al., 2007).

The aim of this work is to develop a multi-criteria model and use a multi-criteria method based on an outranking relation to provide decision support in the diagnosis of dementia related diseases of individuals according to the assessment of their mental status. Taking as a basis the Clinical Dementia Rating (CDR) scale, a tree of criteria has been developed to encompass all the relevant aspects for a comprehensive assessment. A multi-criteria method devoted to the sorting problem and a computer package for helping the analysis have been selected. This decision aid approach expects to receive data (the performance of each individual according to each criterion) from an external assessment system. Other inputs include the technical parameters required by the methodological component. The output consists in the assignment of each individual to a pre-defined ordered category associated with the physical/mental status of the individual.

Furthermore, this enables to carry out a long term analysis of the individual historical data, which may establish a correlation between the model's output and the actual situation. Our approach is aimed at providing a tool for helping technical staff in charge of diagnosing dementia diseases to support making the best decisions, increasing the accuracy and reliability of the evaluation.

The assessment of dementia diseases has been traditionally made using the aggregation of different perspectives of evaluation (criteria) by means of some type of scoring and weighted-sum approaches thus transforming the performances of the entities under evaluation according to the different criteria into a "common value" score (Robert et al., 2010). We believe that in most cases, as in the one under study herein, it is sufficient for analysis and provides more confidence on the results the assigning of the entities under evaluation (individuals) to pre-defined ordered categories of merit rather than producing a single numerical figure. Furthermore, a more detailed analysis within each category is possible whenever it is considered useful to improve the discrimination of the evaluation model.

In this setting it is important to appraise the entities using known standards or profiles. Moreover, it is also convenient to evaluate entities on an "as they come" basis. This capability of evaluating each individual in absolute terms according to reference profiles, and not just in comparison with their peers, as well as the need to include evaluation aspects expressed in different units using different types of scales (also qualitative), can be accomplished using the

ELECTRE TRI method (Mousseau, Slowinski, Zielniewicz, 2000). The ELECTRE TRI method is adequate for our assessment problem because it does not require controversial (scale-dependent) weight specification in order to obtain a single score for each individual and allows the definition of standard profiles (establishing the frontiers between the categories) with which each individual is compared. Those profiles may be updated for further adjustments as required by distinct practical situations. This type of evaluation model can bring advantages to support medical staff in the assessment of dementia diseases in comparison with some traditional processes of applying pre-defined scoring scales.

Other approaches based on multi-criteria models and methods have been proposed in the literature, specifically to assist the process of diagnosing Alzheimer's disease. The work presented in (Castro, Pinheiro, Pinheiro, Tamanini, 2011) proposes a hybrid model combining influence diagrams and multi-criteria methods to compare the values for each entity in a set and then perform a rank within the group. Bayesian Networks are used in (Pinheiro, Castro, Pinheiro, 2008) to serve as a modelling tool for aiding in decision making for the diagnosis of Alzheimer's disease. In (Castro et al., 2011; Pinheiro et al., 2008; Filho, Pinheiro, Coelho, Costa, 2009) good overviews about related works for this area are presented, proposing approaches for decision aiding models applied to medical activities. Moreover, the performance achieved applying methods based on ELECTRE IV and a genetic algorithm is presented in (Filho, Pinheiro, Coelho, 2009; Filho, Pinheiro, Coelho, Costa, 2010). Experiments have been made (Costa, Filho, Coelho, Pinheiro, 2009; Filho et al., 2009) to compare the accuracy and effectiveness of different multi-criteria decision aid methods with different data sets, the conclusions pointing out to some changes in the results for the same models.

The paper is organized as follows. Section 1 provides the interest and motivation of this study. Section 2 presents a brief overview about multi-criteria outranking methods and the software package used in this work to accomplish the goals previously defined. In section 3 the multi-criteria model and the design of the overall approach are presented. Section 4 describes some illustrative results obtained using a case study. Finally, conclusions are drawn and future work is outlined in section 5.

## 2 THE ELECTRE TRI METHOD

The ELECTRE TRI method is a member of the ELECTRE (Elimination and Choice Translating Reality) family of multi-criteria methods (Roy, 1996). ELECTRE methods are based on the construction and exploitation of an outranking relation (“outranking” having the meaning of “is at least as good as”). ELECTRE TRI is devoted to the sorting (classification) problem, which consists in assigning each entity under evaluation to one of a pre-defined set of ordered categories ( $C^1, \dots, C^k$ ), according to several evaluation criteria  $g_j$  ( $j=1, \dots, n$ ). Each entity object of evaluation (individual) is described through a vector of multi-criteria performances. The categories are defined by specifying reference profile vectors ( $b^0, \dots, b^k$ ), being each reference profile  $b^h$  ( $h=1, \dots, k-1$ ) the upper bound of category  $C^h$  and the lower bound of category  $C^{h+1}$ .

The assignment of each entity  $a_i$  to a category  $C^h$  is done by comparing its value in each criterion to the corresponding reference profiles. The method assigns each entity to the highest category such that its lower bound is outranked by  $a_i$ . The outranking relation is verified by comparing a credibility index, computed by using the differences in performance and the criterion weights, with a cutting level  $\lambda$  ( $\lambda \in [0.5, 1]$ ), which defines the “majority requirement” and consequently the exigency of the classification.

In ELECTRE methods weights shall be perceived as true coefficients of importance of the criteria (their “voting power”), which are scale-independent, i.e. not linked to the scales in which each criterion is measured. This is a totally different interpretation of weights with respect to weights used as technical parameters for translating the scores in each criterion into a global score. For further details about ELECTRE TRI see (Mousseau et al., 2000).

The ELECTRE TRI method requires the specification of a set of technical parameters (which convey meaningful preference information): the reference profiles defining the categories ( $b^0, \dots, b^k$ ), the criterion weights  $w_j$ , the cutting level ( $\lambda$ ), a set of indifference ( $q_j$ ), preference ( $p_j$ ) and veto ( $v_j$ ) thresholds for each criterion  $g_j$  and reference profiles. Indifference and preference thresholds characterize the acceptance of imprecision in the judgment by considering two entities as indifferent when their individual performances in each criterion  $g_j$  differ less than a specified amount  $q_j$ . The transition from indifference to preference is not sharp but changes linearly from  $q_j$  to  $p_j$ , this being captured by the criterion concordance index  $c_j$ . Figure 1 illustrates the computation of the criterion

concordance index when comparing alternative  $a$ , and the profile  $b^i$  for criterion  $g_j$ .

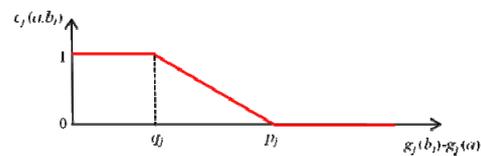


Figure 1: Criterion concordance index.

The veto thresholds are quite relevant in our case study because they capture “non-compensatory” situations in which a very bad performance in any criterion prevents an entity of being classified in the best category or even force it to be classified in the worst category independently of having very good performances in all other criteria. In general, practical evaluation models require the consideration of a certain level of non-compensation, at least for some criteria.

The assignment classification provided as result of ELECTRE TRI is the desired indicator of the disease progress level for each individual. In this paper, we assume that the input data (the performance of each individual in any criterion expressed in a quantitative or qualitative scale) must be supplied by an external system and/or medical inputs. It is advisable that an expert panel, for instance a medical board, could supply the technical parameters (reference profiles, weights and thresholds) referred to above. The overall decision support approach will be discussed in detail in section 3.

## 3 AN APPROACH BASED ON AN OUTRANKING METHOD

Multi-criteria analysis methods are largely unexploited so far on health care, particularly in classification processes using medical information. In our work, a multi-criteria approach using the ELECTRE TRI method is proposed to deal with a model that can use behavioural and cognitive data to infer about the mental and physical state of individuals.

The keystone of this study has been the development of a comprehensive multi-criteria model encompassing all the fundamental axis of evaluation. The structuring phase is an essential step to reach a stable multi-criteria evaluation model from a generally “messy situation” through a process of unveiling and refinement procedure of a

consistent family of criteria. The fundamental criteria that we have selected (tree of criteria) to assess any individual are depicted in Figure 2, in which the operational criteria are inside the boxes. The fundamental criteria, which are dealt with by the method, are derived from a set of sub-criteria identified in the structuring phase. The score of any individual in each fundamental criterion results from a weighted aggregation of the scores in the corresponding sub-criteria. Typically, each sub-criterion is measured in a qualitative scale according to the frequency of occurrences using three levels with the associated meaning of: “it never happens”, “it happens sometimes”, and “it happens very often”.

An external system is responsible for providing the performance of each individual according to each evaluation criterion in a given measurement scale. A group of experts, or medical board, provides the technical parameters required by the method. This can be done in an iterative way for model calibration purposes.

The establishment of a pattern of behaviours that is indicative of the disease status, which can be parameterized, conveys the information to define the reference profiles that define the boundary of the classes. These profiles have been specified by means of scales used in Neuroscience, Psychology, and other related areas, to select which type of behaviours should be used in the evaluation of the mental state of the individual. The CDR scale is one of the most well-known scales used in the process of Alzheimer’s disease diagnosis. This type of scales is applied as questionnaires, which raise the subjectivity issue when the patient or the caregiver is answering to them. The subjectivity inherent to answering the questionnaires is somehow mitigated by means of the use of the indifference, preference and veto thresholds in the operational framework of ELECTRE TRI.

Four categories (classes) have been identified to which any individual will be assigned based on the information about his/her mental and physical performances:

- Urgent (earlier medical intervention is required).
- Disturbing (medical accompanying is needed).
- Mild Impairment (attention shall be paid to evolution).
- Normal (no need to be followed on a regular basis).



Figure 2: Criteria tree.

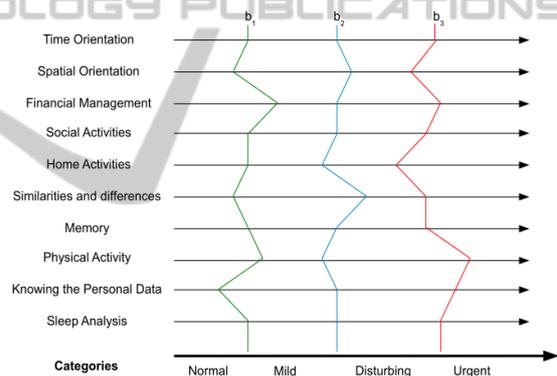


Figure 3: Categories and reference profiles.

If judged necessary more classes can be considered to increase discrimination between statuses. This would imply to define more technical parameters associated with new reference profiles.

Figure 3 outlines graphically the categories bounded by the reference profiles, which each individual is compared with. The reference profiles are displayed in Figure 3 just for illustrative purposes of how categories are defined and they do not represent the actual values used in the experiments whose results are presented in section 4.

Table 1 presents each reference profile ( $b^1$ ,  $b^2$  and  $b^3$ ) and the corresponding criterion performance ( $b_y$  by this order in each criteria), which may be considered as “reference individuals” establishing the frontier between the categories.

Table 1: Criteria and Reference Profiles.

Criteria	Reference Profiles ( $b^1, b^2, b^3$ )
Temporal Orientation	- Do not know the current day - Often does not know the day of the week - Do not know the current day of the week
	- Often does not know the month
	- Does not know the month or - Often does not know the year
Space Orientation	- Often gets lost away from home
	- Lose yourself away from home - Often lost in familiar locations
	- Often confused where currently is - Confused where currently is - Often gets lost inside of the house
	- Cannot give / make accounts of large amounts - Cannot give / make accounts of small amounts - Lose track of the money
Financial Management	- Often does not drive car
	- Left driving car - Decrease in activities outside home - Lack of activities outside home
	- Slight decrease in the level of abstraction - Cannot get basic abstraction - Often does not know
Social Activity	- Failure at the address details - Cannot say all the words - Often misses the address
	- Decrease in motor activity - Sedentary lifestyle - Begins to detect hand tremor
Similarities and differences	- Does not know the birthplace - Does not know the name and location of the last school
	- Does not know / incomplete date of birth - Does not know his education level - Does not know the last job or - Forgot the main profession
	- Issues falling asleep - Waking up too early - Sleeping excessively during the day - Getting up in the night
Memory	- Failure at the address details - Cannot say all the words - Often misses the address
	- Decrease in motor activity - Sedentary lifestyle - Begins to detect hand tremor
Physical Activity	- Does not know the birthplace - Does not know the name and location of the last school
	- Does not know / incomplete date of birth - Does not know his education level - Does not know the last job or - Forgot the main profession
	- Issues falling asleep - Waking up too early - Sleeping excessively during the day - Getting up in the night
Knowing personal data	- Does not know the birthplace - Does not know the name and location of the last school
	- Does not know / incomplete date of birth - Does not know his education level - Does not know the last job or - Forgot the main profession
Sleep Analysis	- Issues falling asleep - Waking up too early - Sleeping excessively during the day - Getting up in the night
	- Issues falling asleep - Waking up too early - Sleeping excessively during the day - Getting up in the night

In order to classify the validity of the outranking relation between the individual and the reference profiles is assessed, thus determining the assignment of the individual to one of the categories. In Table 1 the reference profiles are presented in terms of the meaning associated with the scores in each criterion and not actual values, using the CDR scale as a guideline.

#### 4 SOME ILLUSTRATIVE RESULTS

In order to test our model, data of 20 individuals have been used associated with persons in various stages. We have used the Iris software (Dias and Mousseau, 2003) to implement our method and to test it in distinct scenarios. The data contain information about selected individuals with a very good mental state, others displaying intermediate disease indicators, and others with a bad diagnosis. That is, the entities under evaluation have been selected to span a wide set of conditions to illustrate the operation of the multi-criteria model coupled with the Iris package implementing a version of ELECTRE TRI.

Initially, all the technical parameters required by the method (see sections 2 and 3) have been specified: definition of the categories in which the individuals will be classified; preference, indifference and veto thresholds for each criterion and reference profile; criterion weights; cutting level. Although this specification process may seem to impose a significant burden on the decision makers, these parameters are essential to bear their experience and insightful information into the sorting procedure. Usually these parameters are elicited from decision makers with the aid of an analyst with expertise on the methodological component to ease the elicitation process. Moreover, some of these parameters can be preset (according to experience in previous studies). For instance, indifference and preference thresholds may be established as percentages (e.g., 2% and 10%, respectively) of the value ranges in each class.

Figure 4 presents the results obtained using the Iris package for the cutting level  $\lambda=0.5$ . This means that a “simple majority” of criteria supporting the outranking relation is required. The left column displays the 20 entities under evaluation (individual 0-19) and each column C1–C4 is associated with a category (ordered from the worst to the best one): C1 – Urgent; C2 – Disturbing; C3 – Mild Impairment; C4 – Normal. The partially coloured matrix displays the assignment of each entity to a category. The darker cells represent the assignment proposed by Iris for each individual, which is associated with a central combination of parameters. The lighter cells represent the other possible assignments, which are obtained for other feasible combinations of parameters under certain constraints (in this case, criterion weights that may vary within intervals).

Results	Infer. Prog.   Indices			
	C1	C2	C3	C4
0		█		
1			█	
2	█			
3		█		
4			█	
5				█
6	█	█		
7	█			
8		█	█	
9	█	█		
10				█
11	█			
12		█	█	
13		█	█	
14	█	█		
15			█	
16		█		
17		█		
18				█
19		█	█	

Figure 4: Assignments with  $\lambda=0.5$ .

Analyzing Figure 4, we can conclude, for example, that individual 0 is restricted to category C2 – Disturbing (all sets of weights lead to this result). Individual 1 is assigned to category C3 – Mild Impairment according to the central parameters but he/she can also be sorted into category C2 (since this is feasible for other parameter combinations).

Figure 5 displays the results obtained when using a cutting level  $\lambda=0.85$ , that is, increasing significantly the exigency of the classification derived from the outranking relation verification. Therefore, the assignments proposed by Iris for each entity are now “less favourable”. For example, individual 14 was previously classified in C2, using central parameters, and after the increase of  $\lambda$  his/her assignment is restricted to C1.

More experiments have been done to analyze the effects of changing the criterion weights for testing scenarios in which the contribution for the classification is not equal for all the criteria. That is, we assume that there are criteria more important than others, so they are given a higher “voting power” in ascertaining the outranking relation.

Figure 6 illustrates the results obtained using a cutting level  $\lambda=0.5$  and different criterion weights reflecting the following importance rank (in decreasing order): “Space Orientation” and “Sleep Analysis”; “Financial Management”; “Temporal Orientation” and “Social Activities”; all the other criteria. Comparing the results obtained in Figure 4 and Figure 6 we conclude that individuals 2 and 13 can now attain classes C1 and C2, respectively, and individual 8 can just be assigned to class C2, thus displaying the impact that criterion weight changes can have on the final classification.

Results	Infer. Prog.   Indices			
	C1	C2	C3	C4
0		█		
1			█	
2	█			
3		█		
4			█	
5				█
6	█	█		
7	█			
8		█	█	
9	█	█		
10				█
11	█			
12		█	█	
13		█	█	
14	█			
15			█	
16		█		
17		█		
18				█
19		█	█	

Figure 5: Assignments with  $\lambda=0.85$ .

Results	Infer. Prog.   Indices			
	C1	C2	C3	C4
0		█		
1			█	
2	█			
3		█		
4			█	
5				█
6	█	█		
7	█			
8		█	█	
9	█	█		
10				█
11	█			
12		█	█	
13		█	█	
14	█			
15			█	
16		█		
17		█		
18				█
19		█	█	

Figure 6: Assignments with  $\lambda=0.5$  and with different weights.

The interactive environment provided by Iris may be used, for instance, to assess the trend of the progression of the disease for a given individual. The same individual in different points in time may be considered as different entities under evaluation and the relative assignment is easily assessed. Lighter coloured cells are also indicative that individuals may be close to change to the next categories.

## 5 CONCLUSIONS

This paper presents a multi-criteria model to provide

decision support in the diagnosis process of dementia cases. The model is tackled using a methodology based on an outranking relation, which is exploited for a sorting problem in which individuals are assigned to categories associated with the perceived status of the disease. Categories are defined using references profiles with which individuals are compared to check the outranking relation.

This approach offers the possibility to adjust the reference profiles as well as other technical parameters required by the method to better suit the different usage scenarios. The use of ELECTRE TRI's technical parameters may help to cope with subjectivity issues that are present in the traditional processes of applying pre-defined scales. This multicriteria approach offers a flexible methodology capable of being adjusted according to the objectives of medical staff in the assessment of dementia diseases.

Future developments include using previous examples of classified individuals to infer new reference profiles and classification assignments, analyze thoroughly the reliability of considering "non-central" classifications in the output results as tendency indicators, perform tests with other multicriteria decision aid methodologies to conclude about the reliability achieved when using different approaches.

## REFERENCES

- Castro, A., Pinheiro, P., Pinheiro, M., Tamanini, I. (2011). Towards the Applied Hybrid Model in Decision Making: A Neuropsychological Diagnosis of Alzheimer's Disease Study Case. *International Journal of Computational Intelligence Systems*, 4, (1), 652-656.
- Costa, N., Filho, A., Coelho, A., Pinheiro, P. (2009). Selecting prototypes for two multicriteria classification methods: A comparative study. *World Congress on Nature & Biologically Inspired Computing*. 1702 – 1707.
- Dias, L., Mousseau, V. (2003). *IRIS – Interactive Robustness Analysis and Parameters Interference for Multicriteria Sorting Problems* (Version 2.0). User Manual, Document 1/2003 INESC Coimbra. [http://www.inescc.pt/documentos/DocInt\\_1\\_2003.pdf](http://www.inescc.pt/documentos/DocInt_1_2003.pdf)
- Dias, L., Mousseau, V. (2003). IRIS: A DSS for Multiple Criteria Sorting Problems. *Journal of Multi-Criteria Decision Analysis*, 12, 285-298.
- Filho, A., Pinheiro, P., Coelho, A. (2009). Towards the Early Diagnosis of Alzheimer's Disease via a Multicriteria Classification Model. *Proceedings of the 5th International Conference on Evolutionary Multi-Criterion Optimization*. Springer, 393-406.
- Filho, A., Pinheiro, P., Coelho, A., Costa, N. (2009). Comparison of two prototype-based multicriteria classification methods. *IEEE Symposium on Computational Intelligence in Multi-Criteria Decision-Making*, 133 – 140.
- Filho, A., Pinheiro, P., Coelho, A., Costa, N. (2010). Comparison of Two MCDA Classification Methods over the Diagnosis of Alzheimer's Disease. *Proceedings of the 4th International Conference on Rough Sets and Knowledge Technology*. Springer, 334-341.
- Hendrie, H. (1998). Epidemiology of dementia and Alzheimer's disease. *American Journal Geriatric Psychiatry*, 6, S3-S18.
- Mousseau, V., Slowinski, R., Zielniewicz, P. (2000). A user-oriented implementation of the ELECTRE-TRI method integrating preference elicitation support. *Computers & Operations Research*, 27, 757-777.
- Pinheiro, P., Castro, A., Pinheiro, M. (2008). A Multicriteria Model Applied in the Diagnosis of Alzheimer's Disease: A Bayesian Network. *IEEE International Conference on Computational Science and Engineering*, 15-22.
- Roberson, E., Mucke, L., 2006. 100 Years and Counting: Prospects for Defeating Alzheimer's Disease. *Science*, 314, 781-784.
- Robert, P., Ferris, S., Gauthier, S., Ihl, R., Winblad, B., Tennigkeit, F. (2010). Review of Alzheimer's disease scales: is there a need for a new multi-domain scale for therapy evaluation in medical practice?. *Alzheimer's Research & Therapy*, 2(24).
- Roy, B. (1996). *Multicriteria Methodology for Decision Analysis*. In Kluwer Academic Publishers, Dordrecht.
- Vissera, P., et al. and DESCRIPA study group. (2008). Development of Screening Guidelines and Clinical Criteria for Predementia Alzheimer's Disease. *Neuroepidemiology*, 30 (4), 254-265.
- Wilkins, C., Wilkins, K., Meisel, M., Depke, M., Williams, J., Edwards, D. (2007). Dementia Undiagnosed in Poor Older Adults with Functional Impairment. *The American Geriatrics Society*, 55 (11), 1771-1776.