Measuring social isolation in older adults through Ambient Intelligence and Social Networking Sites

Wilfrido CAMPOS [a], Alicia MARTINEZ [a], Hugo ESTRADA [b], Noe CASTRO [a]
[a] *National Centre for Research and Technology Development, CENIDET, {amartinez, mcwilfrido11c, ncastro}@cenidet.edu.mx*
[b] *Industry Documentation and Information Fund, INFOTEC, {hugo.estrada@infotec.com.mx}*

Abstract. Early diagnosis of social isolation in older adults can prevent physical and cognitive impairment. This diagnosis usually consists on personal and periodic application of psychological assessment instruments. Unfortunately this is often a tedious process and therefore this is a situation that opens up opportunities in creating new ways of diagnosis. In this context, ambient intelligence and social networking sites are suitable technologies for automatic monitoring of significant changes in social interactions of older adults. However, current instruments that measure social isolation are based on subjective aspects since they only evaluate emotional social support and they do not consider objective aspects. This is the reason why a prediction model based on objective isolation variables is needed in order to measure the social interactions through computing mechanisms. This paper presents the development of a prediction model from the social interaction activities that can be registered through smartphone's sensory capabilities, the personal communications using an online social network and also radio-frequency identification mechanisms. The proposed model will benefit institutions interested in developing technological solutions to detect early stages of social isolation and improve the quality of life of older adults.

Keywords. Predictive modelling, social isolation, older adults, ambient intelligence, social networking site**.**

Introduction

One of the more accentuated issues in late adulthood is social isolation, due to factors such as labor retirement, children living in different places, or loss of a spouse. Social isolation is defined as the lack of contact and interaction with others [1]. An early diagnosis of this condition significantly reduces the risk of depression, cognitive impairment, decreased food intake, reduced physical exercise or impoverishment of the social network [2].

This underscores the importance of knowing at all times when an older adult stops socializing, in order to carry out interventions that allow him overcome this disease and be kept in a socially active state.

Currently, there are several psychological instruments, denominated scales, to assess the level of social isolation in older adults. Some of these psychological instruments are: a) Friendship scale: this consists of six Likert questions about perceived social support from family and friends [3]. b) The Social Support Questionnaire: this scale identifies the social support satisfaction, social participation and material aid [4]. c) Inventory of Socially Supportive Behaviors: this instrument assesses instrumental, informational and social support [5]. d) The Lubben Social Network scale: this scale measures social support felt from friends and family in older adults. These instruments share the common objective of assessing the level of social isolation with diagnosis based on a series of subjective questions from social support felt [6].

Unfortunately, the application process of these instruments is tedious because older adults have to go to assistance centers or with specialized people in order to be valued. This situation encourages the development of computer systems that not only bring these instruments to the elder, but also enable automatic monitoring of significant changes in social interactions of older adults.

In this context, Ambient Intelligence (AmI) provides widely accepted computational mechanisms that would help these people in their daily lives in a manner that is simple, that is to say, intelligent [7], and ubiquitous and proactive at the same time. On the other hand, the increase in the participation of older adults in the Social Networking Sites (SNS) opens a range of opportunities to monitor social interactions through these virtual communication places [8]. However, the qualitative values that these psychological instruments evaluate are complex to be obtained automatically by computational mechanisms, for instance: "*With how many relatives does he or she feel comfortable to talk about private matters?*" or "*How many friends does he or she feel close enough to ask for help?*

Therefore, the objective of this research was to develop a predictive model (decision tree) to serve as a baseline for determining social isolation and which is also simple to implement in a computer system. This model receives as input quantitative values from indoor/outdoor social interactions performed by older adults. To achieve this goal, we conducted a non-probability sampling to 160 seniors consisted of: 1) determining the level of social isolation from the Lubben Social Network scale, 2) quantify social interactions through the mobile phone and personal social networking account and 3) quantify staying inside and outside the home.

The proposed model will benefit graduate students, research institutes and companies interested in developing systems to detect early stages of social isolation and improve the quality of life of the elder.

The paper is structured as follows: Section 1 describes the background of this research. In Section 2 is presented the related works that detect social isolation. Section 3 presents the methodology and outcomes and finally, section 4 presents the conclusions and future work.

1. Background

Social isolation

An aging population is a phenomenon faced by many nations, which is derived from declining birth rates and increasing life expectancy. According to the World Health

Organization (WHO), all individuals over 60 years are considered to be elderly people. Mexico is currently undergoing a demographic transition which suggests that by 2050 one in four people will be over 60 years old [9].

One of the most acute problems in late adulthood is socialization, where issues of social isolation are the most frequent and the most threatening to the independent living and mental health of elderly people. Social isolation is defined as the lack of contact and interaction with others [10], and the risks associated with this condition have been compared in magnitude to the dangers caused by smoking and other biomedical and psychosocial risk factors [11]. In turn, these risks increase due to factors such as retirement, children living in different places, suffering the loss of a spouse or close friends, as well as those living alone having a small social network, little participation in social activities, and feelings of loneliness [12, 13].

Predictive models

The main goal of predictive models is to learn from observations and logical constructs. The knowledge obtained is represented by a decision tree, which is used to categorize a number of conditions that occur in succession. The final categorization is the level of social isolation that presents an older adult, for this reason it was important to use a psychological instrument (scale) for evaluating this condition. The Lubben Social Network scale was used in this research because it is a validated psychological mechanism and also it has the advantage over those already mentioned is that this has a translated Spanish language version, thus avoiding translation errors that could cause a different sense the objective of each question.

2. Related Work

Currently, there are several research works that analyze the support that Ambient Intelligence and Social Networking Sites can provide to face the socialization problems.

These researches include topics such as: i) reducing the level of social isolation and increase independent life at home [14],[15],[16], ii) to stimulate the elder's mind to remember past and future events [17], [18], iii) to keep seniors in touch with friends through natural ways of interaction [19],[20], iv) to encourage physical exercise [21], [22],[23] and v) monitoring the state of health and to keep caregivers and relatives informed [24], [25], [26].

However, the issues about measuring social isolation through computational mechanisms has been poorly addressed, considering that an in-situ early diagnosis of this disease might mitigate the risk of depression, cognitive impairment, decreased intake food, reduction of physical exercise, or impoverishment of social network [2]. This underscores the importance of knowing at all times when an adult is leaving socializing, in order to implement interventions that allow overcoming this disease and continue on a socially active state.

3. Method and Results

The activities developed to build the predictive model of social isolation were grouped into two phases: i) sample collection and ii) building the predictive model. A summary of the activities in each phase is shown in Table 1.

Table 1. Phases and activities carried out to develop the predictive model of social isolation.

Phases	i) Sample Collection	ii) Building predictive model
Activities	• Definition of the study group's profile. • Definition of the type sampling. • Selecting assessment instrument of social isolation. • Selecting attributes. • Gathering sample.	• Tabulating results. • Processing data. • Obtaining predictive model (decision tree).

Next, an explanation about each activity and the obtained results is provided.

3.1. Sample collection phase.

The sample collection phase consisted in carrying out a non-probability sampling about social interaction activities performed by older adults inside and outside home. This study focused on the activities that can be registered through the mobile phone, personal social networking account and radio-frequency identification (RFID) mechanisms. Each of the activities is described in this section.

Defining of the study group's profile.

This research project focuses on older adults with full use of their physical and cognitive abilities, so the features that were taken into consideration to be part of the sample are the following:

- Being older adult (60 years or older).
- Person without a disability that prevents walking, using a mobile phone or computer.
- Owning a mobile phone (with minimum capabilities to make calls or send text messages)
- Possess a profile on a social networking site (this feature is optional because there are still few seniors who have a social networking account)

Definition of the study group's profile.

As mentioned in the introductory part of this study, the predictive model is intended to be used as baseline to infer levels of social isolation, this is a reason why this model was built from an exploratory study about social interaction activities performed by older adults through technological mechanisms. Therefore a non-probability sampling was carry out, where the sample selection was a personal and intentional criterion of the research group.

Selecting assessment instrument of social isolation.

One of the necessary attributes to build a predictive model is the value that will yield as result of the classification of the data. For this model, the final result corresponds to different levels of social isolation, these are, absence of social isolation, moderate social isolation, or severe social isolation. The selected instrument was the result of repeated meetings with staff specializing in psychology. Therefore, in order to carry out this assessment the use of the Lubben Social Network scale in its Spanish version was considered. This psychological instrument determines the level of social isolation in older adults ranging from a score from 0 to 30 from 6 questions about social support perceived by the older adult with friends and relatives.

Selecting attributes.

The attributes considered to build the predictive model, were the following: i) demographic information, ii) quantification of social interactions through mobile phone and social networking account, and iii) quantification of stay in areas or places inside and outside the home. As demographic information was considered following aspects: a) age, b) marital status, c) disability, d) gender, e) labor situation, and f) live alone. With regard to the activities of social interaction, Table 2 shows a summary of the attributes classified by computer technology and technological resources:

Table 2. Social interaction activities classified by computer technology and the technological resources used.

<table>
<tr><th>Computer Technology</th><th colspan="2">Technological resources</th><th>Social interaction activity</th><th>Place of activity</th></tr>
<tr><td rowspan="4">Ambient Intelligence</td><td colspan="2">GPS</td><td>Number of places and stay time.</td><td>Outside of home</td></tr>
<tr><td rowspan="2">Mobile phone</td><td>Call log</td><td>Number, frequency and duration of incoming and outgoing calls.</td><td>Inside/outside of home</td></tr>
<tr><td>SMS</td><td>Number and frequency of messages sent and received.</td><td>Inside/outside of home</td></tr>
<tr><td colspan="2">RfId</td><td>Stay time in areas.</td><td>Inside of home</td></tr>
<tr><td rowspan="2">Social Networking Sites</td><td colspan="2">Wall</td><td>Number and frequency of published and received commentaries (post).</td><td>Inside/outside of home</td></tr>
<tr><td colspan="2">Chat</td><td>Number and frequency of sessions started or received.</td><td>Inside/outside of home</td></tr>
</table>

Altogether, a questionnaire, in Spanish language, with 48 questions was built and backed by psychology staff for their application (The whole questionnaire can be retrieved from http://goo.gl/vCf2CT).

Gathering sample.

This activity consisted of applying the questionnaire personally in places where seniors attend by themselves in a voluntary manner, because the requirement of being in full possession of their physical and cognitive abilities was considered a part of the study group's profile. For this reason, we did not consider places where the elderly are forced to stay like hospitals or nursing homes. The sample was collected in Cuernavaca city, Morelos, México. The places were: i) public parks, ii) malls and ii) entertainment places.

The questions formulated by the assessment tool require to consider information which is at least one month old, situation which makes it difficult for older adults to remember accurate figures on their social interactions in this periods, therefore the respondent was asked to provide the same information in periods of weeks, later during the compiling of the data, this value was multiplied by four (weeks of the month).

One hundred forty four questionnaires were applied to the same number of older adults, including men and women aged between 60 and 89 years ($\mu = 68.2$, $\sigma = 8.9$). Figure 1 shows a summary of the sample's general information. In this chart we can observe that the prediction model was generated from: i) 48 severe cases of social isolation, ii) 93 moderate cases of isolation and iii) 3 absence cases of social isolation.

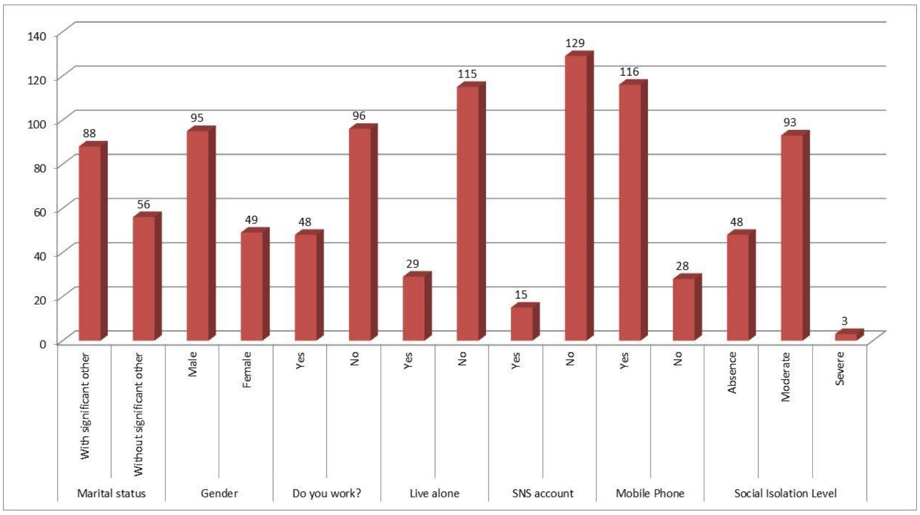

Figure 1. Sample general information.

As the data were compiled, it was inevitable to appreciate the characteristics of each of the assessed social interactions. For instance, in Table 3 we can observe that the socially active elderly are more likely to perform at least one visit away from home per month, while the probability for those who have some degree of social isolation is almost null.

Table 3. Minimum and maximum values for the number, frequency and time stay in places outside the home.

		Minimum number of places visited	**Maximum number of places visited**	**Minimum number of times that makes visits.**	**Maximum number of times that makes visits.**	**Minimum stay time. (hrs)**	**Maxim um stay time. (hrs)**
Social Isolation Level	High risk of social isolation	0	5	0	76	0	384
	Low risk of social isolation	0	5	0	90	0	283
	Absence of social isolation	1	2	2	60	2	180

Another outstanding aspect of social interactions activities corresponds to the use of mobile phones. Table 4 shows the same average amount between incoming and outgoing calls at all levels of social isolation, which means that older adults have generated strong emotional ties with their contemporary friends, however there is still a slight inclination towards maintaining a closer relationship with relatives.

Table 4. Average amount between incoming and outgoing calls from relatives and friends.

		Average amount of incoming calls from relatives	Average amount of outgoing calls from relatives	Average amount of incoming calls from friends	Average amount of outgoing calls from friends
Social Isolation Level	High risk of social isolation	42.7	20.5	21.0	9.4
	Low risk of social isolation	52.8	37.9	36.2	32.2
	Absence of social isolation	400.0	104.0	201.3	80.3

3.2. Development phase of the predictive model.

The development phase of the predictive model consisted of design a database for storing the results of the questionnaires. Subsequently, data mining techniques were used to process this information, giving rise to the predictive model.

Tabulating results.

The questionnaires were applied in paper, therefore the compilation of results were carried out on a spreadsheet, so that a CSV file (*comma separated values*) was built in order to serve as input to a tool for data mining.

Processing data.

This was a key activity in the development of the predictive model, since it consisted of the analysis of the data through the data mining tool named Weka. This tool is one of the most used in this type of studies because it includes a variety of classifiers algorithms for building predictive models [27]. The Weka J48 algorithm is an implementation of the C4.5 algorithm, one of the most widely used data mining algorithms [28], for these reasons the algorithm was considered for developing the model.

The tests made for identifying the appropriate parameters of the J48 algorithm for developing the model included: i) A training set, ii) Cross-validation and iii) Percentage split. Table 5 details the results obtained from these tests.

Table 5. Parameter test sumary.

Test mode	Correctly Classified Instances (%)	Incorrectly Classified Instances (%)	Kappa statistic	Mean absolute error
Use training set	93.05	6.94	0.8520	0.0737
Cross-validation (10 folds)	56.25	43.75	0.1048	0.2872
Percentage Split (60%)	51.72	48.27	0.0092	0.3274

As can be observed in the results shown in the above table, the test mode "Use training set" was the configuration where the best results were delivered. The algorithm classifies 134 instances, which means 93.05% of correctly classified instances, compared to 6.944 % corresponding to 10 of unclassified instances. Therefore "Use training set" was the test mode (settings) used to build the prediction model.

Figure 2 shows the screenshot of test mode "Use training set" where each of the results obtained with the Weka tool is detailed.

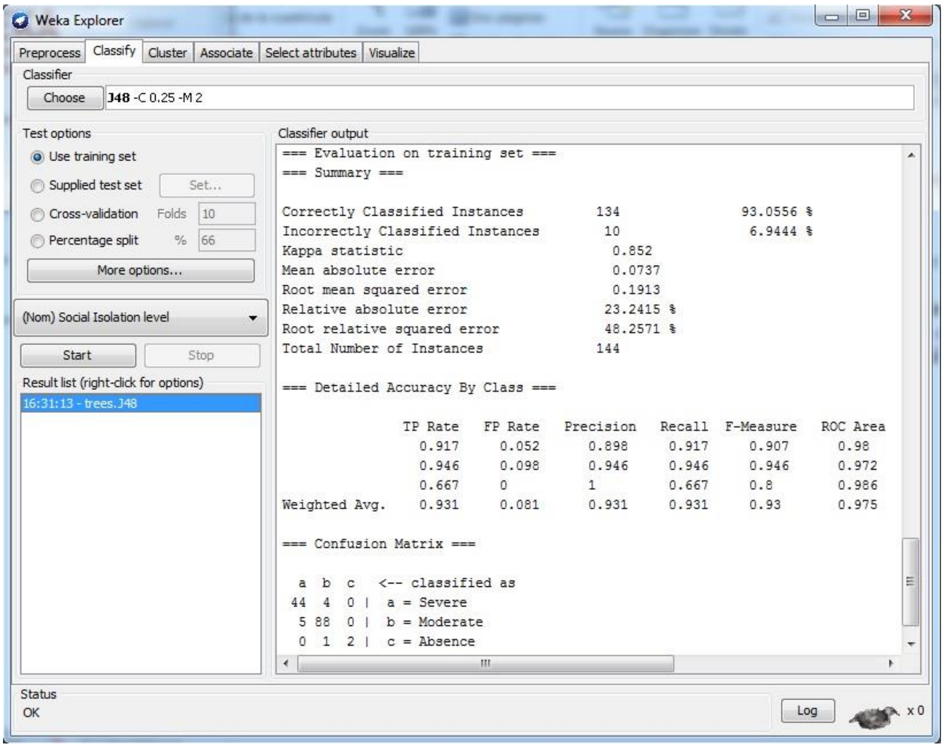

Figure 2. Screenshot of test mode "Use training set" used to build the predictive model.

Obtaining the predictive model (decision tree).

Once the data were processed, this activity consisted of obtaining the visual and formal representation of the predictive model through the WEKA tool.

Figure 3 shows the visual representation of the predictive model (decision tree) and it consists of 24 sheets. That means there are 24 possible inferences of social isolation (absence of social isolation, moderate social isolation, or severe social isolation).

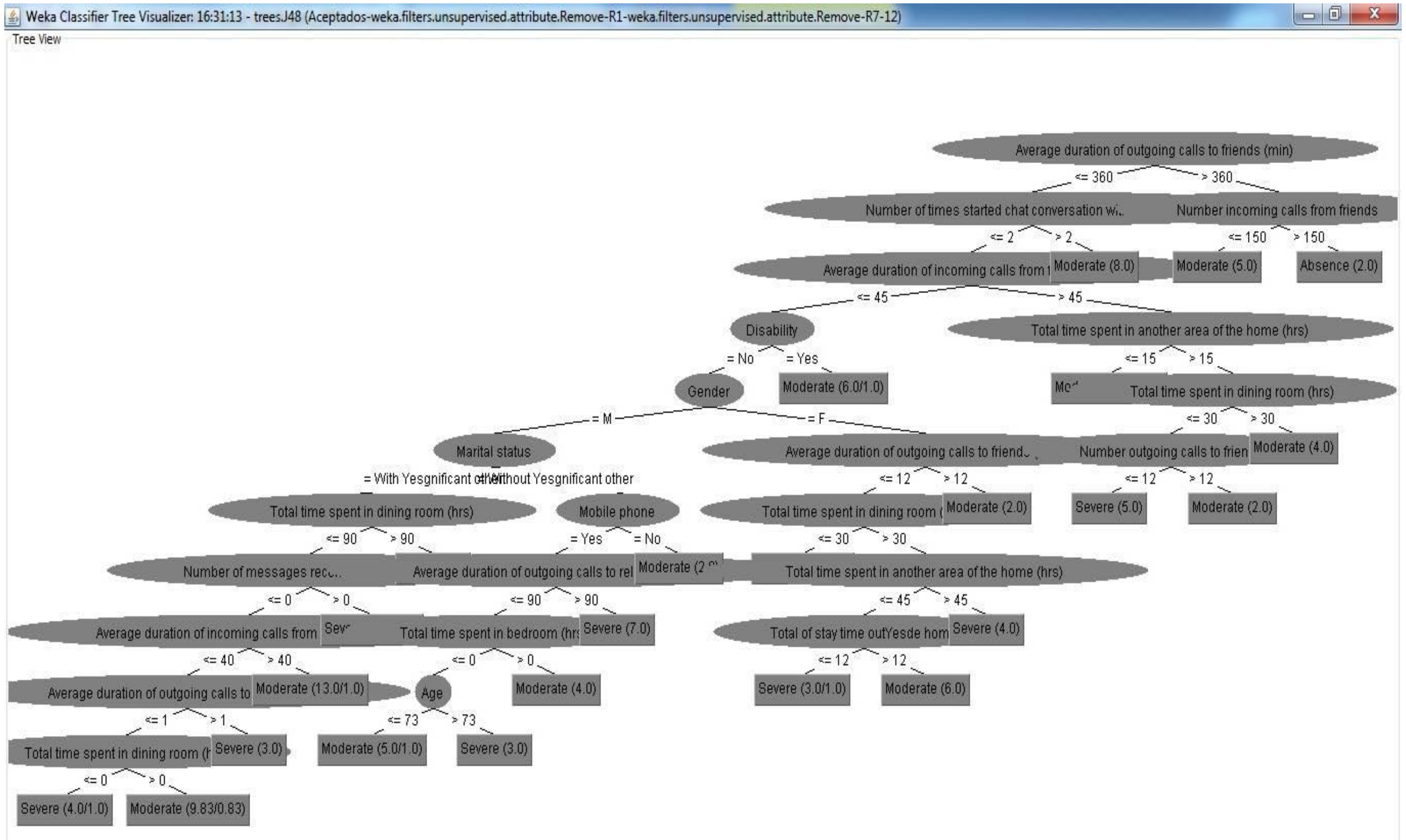

Figure 3. Visual representation of social isolation predictive model for older adults.

Regarding formal representation, a list of formal rules that represents the model is shown in Table 6. It should be noted that, after the analysis of the original 48 questions forming the instrument, only 38 attributes were considered relevant by tool WEKA to infer the different levels of social isolation. Therefore, in the rules shown below only relevant attributes are included.

Table 6. Formal representation of social isolation predictive model.

Row	Rule
1	Average duration of outgoing calls to friends (min) < = 360
2	| Number of times started chat conversation with the relatives < = 2
3	| | Average duration of incoming calls from friends (min) < = 45
4	| | | Disability = No
5	| | | | Gender = F
6	| | | | | Average duration of outgoing calls to friends (min) < = 12
7	| | | | | | Total time spent in dining room (hrs) < = 30: High Risk
8	| | | | | | Total time spent in dining room (hrs) > 30
9	| | | | | | | Total time spent in another area of the home (hrs) < = 45
10	| | | | | | | | Total time of stay inside home (hrs) < = 12: High Risk
11	| | | | | | | | Total time of stay inside home (hrs) > 12: Low Risk
12	| | | | | | | Total time spent in another area of the home (hrs) > 45: High Risk
13	| | | | | Average outgoing calls to friends (min) > 12: Low Risk
14	| | | | Gender = M
15	| | | | | Marital status = Without significant other
16	| | | | | | Mobile Phone = Yes
17	| | | | | | | Average duration outgoing calls to relatives (min) < = 90
18	| | | | | | | | Total time spent in bedroom (hrs) < = 0
19	| | | | | | | | | Age < = 73: Low Risk
20	| | | | | | | | | Age > 73: High Risk
21	| | | | | | | | Total time spent in bedroom (hrs) > 0: Low Risk
22	| | | | | | | Average duration outgoing calls to relatives (min) > 90: High Risk
23	| | | | | | Mobile Phone = No : Low Risk
24	| | | | | Marital status = With significant other
25	| | | | | | Total time spent in dining room (hrs) < = 90
26	| | | | | | | Number of messages received from relatives < = 0
27	| | | | | | | | Average duration incoming calls from relatives (min) < = 40
28	| | | | | | | | | Average duration outgoing calls to friends (min) < = 1
29	| | | | | | | | | | Total time spent in dining room (hrs) < = 0: High Risk
30	| | | | | | | | | | Total time spent in dining room (hrs) > 0: Low Risk
31	| | | | | | | | | Average duration outgoing calls to friends (min)> 1 : High Risk
32	| | | | | | | | Average duration incoming calls from relatives (min) > 40 calls : Low Risk
33	| | | | | | | Number of messages received from relatives > 0: High Risk
34	| | | | | | Total time spent in dining room (hrs) > 90: High Risk
35	| | | Disability = Yes: Low Risk
36	| | Average duration of incoming calls from friends (min) > 45
37	| | | Total time spent in another area of the home (hrs) < = 15: Low Risk
38	| | | Total time spent in another area of the home (hrs)> 15
39	| | | | Total time spent in dining room (hrs) < = 30
40	| | | | | Number of outgoing calls to friends < = 12: High Risk
41	| | | | | Number of outgoing calls to friends> 12: Low Risk
42	| | | | Total time spent in dining room (hrs) > 30: Low Risk
43	| Number of times started chat conversation with relatives > 2: Low Risk
44	Average duration of outgoing calls to friends (min) > 360
45	| Number of incoming calls from friends < = 150 : Low Risk
46	| Number of incoming calls from friends> 150 : No Social Isolation
	Number of Leaves : **24**
	Size of the tree: **47**

As we can observe in above table, the J45 algorithm took into account only the attributes considered significant to generate the set of rules. Within the rules obtained, we can observe that those older adults who frequently communicate by phone with friends (line 1 of the set of rules), are less likely to suffer from social isolation, this is because the vast majority of adults surveyed said maintaining strong ties friendship with his contemporary friends. On the contrary, the rule of line 12 of rules shows that older adults who spend time in another area of the home (for instance, a library or a workshop) always have some degree of social isolation. The same applies to those with a disability (eg, vision problems, or frequent fatigue) because, before the development of an activity outside the home, prefer to stay at home to avoid being a burden to family.

4. Conclusions and future work

This paper presents the development of a social isolation predictive model based on the quantification of social interactions activities that can be registered using ambient intelligence mechanisms and social networking sites. The model was generated as results of an assessment, which used the Lubben Social Network scale and a set of relevant attributes. 144 questionnaires were applied in order to firstly determining the level of social isolation. Secondly to quantify social interactions through the mobile phone and personal social networking account and finally the questionnaires were used to quantify the activities that older adults perform inside and outside the home.

The main advantage of our whole approach consist in to use of an Ambient Intelligence (AmI) approach, which provides computational mechanisms that would help these people in their daily lives in a manner that is simple, that is to say, intelligent, and ubiquitous and proactive at the same time. On the other hand, the increase in the participation of older adults in the Social Networking Sites (SNS) opens a range of opportunities to monitor social interactions through these virtual communication places.

As future work, we consider implementing the predictive model proposed in a computer system. This system will automatically record and evaluate the objective variables related to the social interactions of the elderly. Also, in order to increase the level of system reliability, we recommend to improve the quality of the sample, that is to say, to carry out a probability sampling to make general statements about the social behavior of the elderly. Then incorporate this new knowledge through learning methods to update and strengthen the proposed predictive model, which has been so far considered as baseline.

References

[1] P. Townsend, The family life of old people: an investigation in east London. *The Sociological Review*. **3**(1955), 175-195.

[2] C. Erin York, J.W. Linda, Measuring Social Isolation Among Older Adults Using Multiple Indicators From the NSHAP Study. *Journals of Gerontology: Series B*. **64**(2009), 38-46.

[3] G. Hawthorne, Measuring Social Isolation in Older Adults: Development and Initial Validation of the Friendship Scale. *Social Indicators Research*. **77**(2006), 521-548.

[4] I.G. Sarason, et al., Assessing Social Support: The Social Support Questionnaire. *Journal of Personality & Social Psychology*. **44**(1983), 127-139.

[5] J. Stokes, D. Wilson, The inventory of socially supportive behaviors: Dimensionality, prediction, and gender differences. *American Journal of Community Psychology*. **12**(1984), 53-69.

[6] J. Lubben, M. Gironda, *Social Networks and Social Exclusion: Sociological and Policy Perspectives*, Measuring Social Networks and Assessing their Benefits, 2004, Ashgate Publishing Company: Burlington, VT. 20-34.

[7] J.C. Augusto, *Intelligent Computing Everywhere*, Ambient Intelligence: The Confluence of Ubiquitous/Pervasive Computing and Artificial Intelligence, A. Schuster, Editor, 2007, Springer London. 213-234.

[8] R. Cornejo, J. Favela, M. Tentori, *Ambient displays for integrating older adults into social networking sites*, in *Proceedings of the 16th international conference on Collaboration and technology*2010, Springer-Verlag: Maastricht, The Netherlands. p. 321-336.

[9] C.G. González, *Demografía de envecimiento: argumentos, problemas, temas no cubiertos y horizontes de investigación en México*, Instituto de Geriatría, Secretaría de Salud, México, 2010

[10] R.S. Weiss, D. Peplau, Issues in the study of loneliness, in Loneliness: A Source Book of Current Theory, Research, and Therapy. *Accident Analysis & Prevention*, (1982), 71-80.

[11] J.S. House, Social Isolation Kills, But How and Why? *Psychosomatic Medicine*. **63**(2001), 273-274.

[12] E. York Cornwell, L. J. Waite, Social Disconnectedness, Perceived Isolation, and Health among Older Adults. *Journal of Health and Social Behavior*. **50**(Marzo 2009), 31–48.

[13] J.S. House, D. Umberson, Social relationships and health. *Science New Series*. **241**(1988), 540.

[14] M. Heerink, et al., Assessing Acceptance of Assistive Social Agent Technology by Older Adults: the Almere Model. *International Journal of Social Robotics*. **2**(2010), 361-375.

[15] J.M. Beer, L. Takayama, *Mobile remote presence systems for older adults: acceptance, benefits, and concerns*, in *Proceedings of the 6th international conference on Human-robot interaction*2011, ACM: Lausanne, Switzerland. p. 19-26.

[16] A. Kristoffersson, et al., *Sense of presence in a robotic telepresence domain*, in *Proceedings of the 6th international conference on Universal access in human-computer interaction: users diversity - Volume Part II*2011, Springer-Verlag: Orlando, FL. p. 479-487.

[17] C. Descheneaux, H. Pigot, *Interactive Calendar to Help Maintain Social Interactions for Elderly People and People with Mild Cognitive Impairments*, in *Proceedings of the 7th International Conference on Smart Homes and Health Telematics: Ambient Assistive Health and Wellness Management in the Heart of the City*2009, Springer-Verlag: Tours, France. p. 117-124.

[18] T. Apted, J. Kay, A. Quigley, *Tabletop sharing of digital photographs for the elderly*, in *Proceedings of the SIGCHI conference on Human Factors in computing systems*2006, ACM: Montreal, Québec, Canada. p. 781-790.

[19] H. Pensas, et al., *AMCOSOP: a social networking system for the elderly*, in *Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments*2011, ACM: Tampere, Finland. p. 329-331.

[20] T.-H. Tsai, et al., *Connecting communities: designing a social media platform for older adults living in a senior village*, in *Proceedings of the 6th international conference on Universal access in human-computer interaction: users diversity - Volume Part II*2011, Springer-Verlag: Orlando, FL. p. 224-233.

[21] Y.-L. Theng, et al., *An exploratory study on senior citizens' perceptions of the Nintendo Wii: the case of Singapore*, in *Proceedings of the 3rd International Convention on Rehabilitation Engineering \& Assistive Technology*2009, ACM: Singapore. p. 1-5.

[22] T. Bekker, J. Sturm, E. Barakova, Design for social interaction through physical play in diverse contexts of use. *Personal Ubiquitous Comput.* **14**(2010), 381-383.

[23] E. Nazzi, T. Sokoler, *Walky for embodied microblogging: sharing mundane activities through augmented everyday objects*, in *Proceedings of the 13th International Conference on Human Computer Interaction with Mobile Devices and Services*2011, ACM: Stockholm, Sweden. p. 563-568.

[24] J.M. David, et al., *Living with pain, staying in touch: exploring the communication needs of older adults with chronic pain*, in *Proceedings of the 2011 annual conference extended abstracts on Human factors in computing systems*2011, ACM: Vancouver, BC, Canada. p. 1219-1224.

[25] R. Neßelrath, et al., *Supporting Persons with Special Needs in their Daily Life in a Smart Home*, in *Proceedings of the 2011 Seventh International Conference on Intelligent Environments*2011, IEEE Computer Society. p. 370-373.

[26] I. Marcelino, A. Pereira, *Elder Care Modular Solution*, in *Proceedings of the 2009 Second International Conference on Advances in Human-Oriented and Personalized Mechanisms, Technologies, and Services*2009, IEEE Computer Society. p. 1-6.

[27] A.K. Yadav, H. Malik, S.S. Chandel, Selection of most relevant input parameters using WEKA for artificial neural network based solar radiation prediction models. *Renewable and Sustainable Energy Reviews*. **31**(2014), 509-519.

[28] I.H. Witten, E. Frank, M.A. Hall, *Data Mining: Practical Machine Learning Tools and Techniques (Third Edition)*, Chapter 10 - Introduction to Weka, I.H. Witten, E. Frank, and M.A. Hall, Editors., 2011, Morgan Kaufmann: Boston. 403-406.